CHAPTER-6

MEASURING THE EFFICIENCY OF ENERGY CONSUMPTION OF INDIAN MANUFACTURING SECTOR: A DEA-BASED MALMQUIST PRODUCTIVITY ANALYSIS

The previous chapter examined the interlinkages between energy inputs and industrial value-added for Indian industries for the sample period of 2001-2021. The obtained results revealed that investigation at the disaggregated level implied an increase in gross industrial value-added had a positive impact on the demand for coal usage and electricity consumption at a 5% significance level in the long run. It was also evident that coal & electricity are used as critical components in industrial production both in the short run and long run. In this scenario, it warrants investigating the level of energy efficiency in the manufacturing sector as they are consuming more primary energy. This effort has been undertaken in this chapter.

6.1 Introduction

In formulating its growth strategy, India placed a strong emphasis on developing its industrial sector. The goal was to generate faster growth in the industrial sector (particularly manufacturing) to boost the industry's share of GDP and India's share of global industrial production. This ‘industry-led growth' can only be accomplished by making extensive use of energy. The Indian industrial sector consumes a significant amount of primary energy, accounting for 41 percent of global industrial energy use. As the economy grows, this percentage is expected to rise even more. As a result, India has become the third-largest energy consumer globally after the USA and China.

Furthermore, due to modernization, rapid economic growth, expansion of industry, population growth, and urbanization that has occurred in the previous few decades, energy consumption has rapidly expanded. From 1990 to 2020, India's primary energy demand tripled, amounting to about 916 million tonnes of oil equivalent. Coal is the most common energy source, accounting for over 45 percent of total energy consumption, followed by petroleum and other liquids, biomass wastes, and other renewable energy sources. Manufacturing industries (which are divided into 23 groups) are among the most energy-intensive businesses in India.[1]Even though this sector provides 15 to 17 percent of GDP, it consumes up to 60 percent of all commercial energy.

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[1]These are Manufacturing of Basic Metal, Beverages, Chemical and Chemical Products, Coke and Refined Petroleum Products, Computer and Electronic Optical products, Electrical Equipment, Fabricated Metal Products except Machinery and Equipment, Manufacturing of Food Products, Manufacturing of furniture, Manufacturing of leather related products, Manufacturing of machinery and equipment, Other Non-Metallic Mineral products, Manufacturing of paper and paper products, Pharmaceutical medical, chemical & botanical products, Rubber plastic product, Manufacturing of textiles, Manufacturing of tobacco products, Manufacturing of wearing apparels, Manufacturing of wood and wood products, Other manufacturing, printing and reproduction of media, Publishing Activities, and Crop animal production and Hunting related.

As one of the world's largest and fastest-growing developing countries, India faces the risk of an imminent energy crisis, necessitating prompt action. In such circumstances, the concepts of energy efficiency and energy intensity are brought into sharp focus to maintain energy security while remaining environmentally friendly. India's manufacturing industry has one of the highest energy intensity levels in the world, implying massive energy use. As a result, one of the difficulties is reducing the energy intensity of Indian manufacturing industries. The higher the energy intensity, i.e., the more energy used per unit of output, the lower the energy efficiency. Energy supply is insufficient, energy demand is excessive, and energy demand is price elastic. Therefore, introducing efficiency to the industrial sector is almost unavoidable nowadays. Furthermore, industrial energy consumption is expected to increase at a quicker rate than total final energy consumption. In such a situation, significant effort must be made to improve the industrial sector's energy consumption efficiency to meet tremendous demand.

With this background, the present chapter attempts to estimate energy use efficiency in the Indian manufacturing industry, the highest energy-intensive sector among all other sectors in India. Energy efficiency is understood to mean using energy most cost-effectively to carry out the manufacturing process or provide a service, whereby wastage of energy is minimized. The overall consumption of primary energy resources is reduced. In other words, energy-efficient practices or systems seek to use less energy while conducting any energy-dependent activity and at the same time minimize the corresponding (negative) environmental impacts of energy consumption. In short, energy efficiency indicates the productivity of the input used.

Productivity can be the ratio of industrial output to total energy input. Generally, total factor productivity, which is described as an index of all the output to all the input, has been used to measure production efficiency. Similar to this, the Malmquist productivity index is used, which is part of a data envelopment model based on a non-parametric, linear programming method of distance functions that are often employed to estimate the total factor productivity changes. Choosing the data envelopment model is that it does not require any prior assumption to perform. The MPI decomposes changes in technical efficiency and efficient production frontier shifts. Thus the DEA-based MPI is best suitable for measuring the productivity of energy consumption in the Indian manufacturing sector.

The rest of the chapter is presented in five sections. The second section deals with a literature review purely containing the topic-centric past studies. The third section presents the data source and the methodology. The fourth section discusses the outcome of the result of data analysis. Finally, the conclusion part summarizes the fundamental research in a nutshell with policy recommendations.

6.2 Literature Review

Several studies conducted in the past utilized the DEA-based Malmquist productivity index to measure the level of efficiency in many industries, such as banking, insurance, coal mining, and in the manufacturing sector. It was Farrell (1957) who first floated the idea of measurement of productive efficiency. Later Caves et al (1982) generated index number procedures for comparing Malmquist input-output and productivity for structures of production with a return to scale, productivity changes, and substitution possibilities. Another study was conducted by Fare et al. (1992) for the Swedish manufacturing of pharmacies to measure the total factor productivity for the period from 1980 to 1989, with the help of the Malmquist productivity index. In the recent past, several studies were conducted for measuring the energy efficiency of the manufacturing sectors. These are reviewed below.

Parikh and Kulshreshtha (2002) studied the efficiency and productivity of the Indian coal sector using detailed input and output data for underground and opencast coal mining for the period between 1985 and 1997. They adopted data envelopment analysis (DEA) using the Malmquist index by decomposing productivity change into efficiency and technical change. Their results go against the common understanding that the opencast (OC) mining channelizes more productivity growth than underground mining in India. An increasing percentage of opencast mining regions led to a decline in efficiency throughout the investigation period. Underground mines seemed to have fitted a more efficient practice of functioning to equate to the lag in technical change. On the other hand, the operational efficiency of opencast mines seemed to have been undermined in the process of increasing production through technological progress in opencast mining.

Makridou et al. (2016) on the other hand measured the energy efficiencies of five energy-intensive industries namely construction, power, manufacturing, and transportation for the European Economy between 2000 to 2009. They also employed DEA combined with the

Malmquist Productivity Index to capture the energy efficiency and technical change over the period. The results revealed that there was an overall improvement in energy efficiency across all sectors during the period and efficiency improvement was purely due to technical factors. Moreover, it was found that the energy price and energy taxes negatively influenced the industrial output.

Jebali et al. (2017) examined the energy efficiency responsible factors in Mediterranean countries between 2009 to 2012. In the process of capturing both the bias and serial correlation of efficiency scores, they used the double bootstrap method of Simar and Wilson (2007). In the first stage, empirical results showed that energy efficiency levels in Mediterranean countries are high and declining over time. The results of the second stage analysis indicated that the gross national income per capita, the population density, and the non-conventional energy use impact energy efficiency.

Xu and Wu (2019) performed a statistical analysis of the energy efficiency of the Chinese industrial sector for the reference period of 2010 to 2014. The study was also carried out based on the Data envelopment analysis. The test results revealed that most of the manufacturing sector's energy efficiency was poor, particularly the power sector.

In contrast, Wang et al. (2019) calculated the energy efficiency of 25 developed and developing countries with carbon dioxide (CO_2) emissions as well as their improvement in energy efficiency. Initially, the DEA slack-based model (SBM) was utilized to obtain efficiency scores combined with the Malmquist Productivity Index (MPI) from 2010 to 2017. The variables chosen for the study were the gross national output, Co_2 emission, and energy use. The findings revealed that India and China, being the two largest population countries, attained progress in energy intensity during 2010–2017; however; their energy consumption and CO_2 emissions continued to be more, labeling them to be the two worst countries in terms of energy efficiency.

The analysis of the aforementioned empirical setting reveals the value and use of the data envelopment model in evaluating energy efficiency in the manufacturing industry. Studies on the Indian manufacturing industry are, nevertheless, few. Hence in this chapter, an effort is made to measure energy efficiency and the differences among various industrial manufacturing sectors of the Indian economy.

6.3 Data Source and Methodology

The study spans the years 2001 to 2020 and focuses on a group of 23 manufacturing decision-making units. The required data was obtained from India's Annual Industrial Survey. Coal consumption (CC), electricity consumption (EC), petroleum consumption (PC), other oil consumption (OC), and industrial value added (VA) were among the variables used. For undertaking the analysis, a disaggregated analysis is undertaken at the level of individual manufacturing units and manufacturing groups. The input-output table has been worked out for each decision-making unit based on the energy consumed and gross industrial value added for the various variables stated above. As a corollary, there is just one output table and four input tables. The Deap-xp2 computer application was used to run this input-output table.

For the measurement of the productivity of energy consumption in Indian manufacturing sectors the DEA-based Malmquist Productivity Index (MPI) has been used in this study. The MPI is a distance function that enables to the analysis of multi-input and multi-output systems without any assumption of the production behavior. Here it is to be noted that the distance function can be defined as either input-based or output based. In this chapter, we focus on the input-based distance function to measure the MPIs for calculating the energy consumption performance of different Manufacturing sectors in India and the distance to the efficient production frontier (EPF) for the inefficient Decision-Making Units.

Suppose x and y are the input and output vectors, respectively. $S^t(y)$ is the efficient production frontier. $\theta$is the ratio of input reduction for moving to the EPF. Hence the distance function can be defined as below:

$$D^t(x^t, y^t) = \max\{\theta \left| \frac{x^t}{\theta} \in S^t(y)\right\} \quad (1)$$

The MPIs in period *t* can be defined as

$$\text{MPI}=\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \quad (2)$$

Where $D^t(x^t, y^t)$ is the distance function for measuring the distance from the position in the input and output space of the period t to the EPF at time t...$D^t(x^{t+1}, y^{t+1})$is the distance function for measuring the distance from the position at period t+1 to the EPF at time t.

The MPIs in period *t+1* can be defined as:

$$\text{MPI}=\frac{D^{t+1}(x^{t+1},y^{t+1})}{D^{t+1}(x^t,y^t)} \qquad (3)$$

Where $D^{t+1}(x^{t+1}, y^{t+1})$ is the distance function for calculating the distance from the position in the input and output space at period t+1 to the EPF at time t+1.$D^{t+1}(x^t, y^t)$is the distance function for estimating the distance from the position at period t to the EPF at time t+1.

Farrell (1989) denoted the Malmquist productivity index as

$$MPI_0 = \left[\frac{D_0^t(x_0^t,y_0^t)}{D_0^t(x_0^{t+1},y_0^{t+1})}\frac{D_0^{t+1}(x_0^{t+1},y_0^t)}{D_0^{t+1}(x_0^{t+1},y_0^{t+1})}\right]1/2 \qquad (4)$$

In this paper, the MPI can be used to estimate the change in energy consumption of different manufacturing units in India for the period between t and t+1. If $\text{MPI}_0>1$, progress in efficiency; If $\text{MPI}_0 =1$, then efficiency remains constant, and efficiency decreases if $\text{MPI}_0 <1$.

To find out the reasons for MPI change, we follow Fare et al[2] and disaggregate the MPI into two components. Along with that, we have used a similar method to check efficiency change and technical change, namely;

$$\text{MPI}_0 = \frac{D_0^t(x_0^t,y_0^t)}{D_0^{t+1}(x_0^{t+1},y_0^{t+1})}\left[\frac{D_0^{t+1}(x_0^{t+1},y_0^{t+1})}{D_0^t(x_0^{t+1},y_0^{t+1})}\frac{D_0^{t+1}(x_0^t,y_0^t)}{D_0^{t+1}(x_0^t,y_0^t)}\right]1/2 \qquad (5)$$

Among the two components the first component calculates the degree of technical efficiency change (TEC) from the period t and t+1, namely:

$$\text{TEC}_0 = \frac{D_0^t(x_0^t,y_0^t)}{D_0^{t+1}(x_0^{t+1},y_0^{t+1})} \qquad (6)$$

[2]R. F¨are, S. Grosskopf, B. Lindgren, and P. Roos, "Productivity changes in Swedish pharamacies 1980–1989: a non-parametric Malmquist approach," *Journal of Productivity Analysis*, vol. 3, no. 1-2, pp. 85–101, 1992.

TEC estimates the catch-up effect, which indicates the energy consumption performance in the indicated period. Whereas the second component measures the efficiency production frontier shift (EPF) between the period t and t+1 namely,

$$\mathrm{EPFS}_0 = \left[\frac{D_0^{t+1}(x_0^{t+1}, y_0^{t+1})}{D_0^{t}(x_0^{t+1}, y_0^{t+1})} \frac{D_0^{t+1}(x_0^{t}, y_0^{t})}{D_0^{t+1}(x_0^{t}, y_0^{t})}\right] 1/2 \quad (7)$$

EPFS calculates the frontier-shift effect, which shows the shift in the production technology of the industry. If $EPFS_0>1$, then it means a positive shift of EPF or technical progress. $EPFS_0<1$ indicates a negative shift of EPF or technical regression. If $EPFS_0= 1$, then the EPF is constant. As per the above theoretical background, MPI can be constructed as follows:

$$MPI_0= TEC_0.EPFS_0 \quad (8)$$

At first, we estimate the MPI of a decision-making unit to measure the distance to EPF. To perform this, we will employ the DEA model to estimate the distance function. The aim of using this approach is to calculate the energy consumption efficiency and the ratio of input reduction for reaching the EPF. The following model can be used to measure the performance in a period and the distance can also be calculated. Suppose we have nDMUs, each DMU_j (j=1, 2, 3, . . ., n) produces a vector of outputs by using a vector of inputs at each period t, t = 1, . . ., T. The DEA model at time period$t$can be expressed as follows:

$$D_0^t(x_0^t, y_0^t) = Min\theta_{0,}$$
$$\text{s.t} \sum_{j=1}^{n} \lambda_j x_j^t \le \theta_0 x_0^t,$$
$$\sum_{j=1}^{n} \lambda_j y_j^t \ge y_0^t, \quad (9)$$
$$\lambda_j \ge 0, \ \ j = 1, \dots, n,$$

Where $x_0^t = (x_{10}^t, \dots, x_{m0}^t)$ and $y_0^t = (y_{10}^t, \dots, y_{s0}^t)$is the input and output vectors of DMU_0 among others. Here we need to understand that DEA models used in the Malmquist productivity index can be either input-oriented or output oriented. Hence in this research input-oriented model has been employed. So, this model considers possible radial reductions of inputs when the outputs are kept constant at the current level, this is nothing but shows the amount of energy consumption reduction when industrial value added is fixed. Model (1), $\theta_0^*(\theta_0^* = D_0^t(x_0^t, y_0^t))$ is the efficiency of DMU_0at time period$t$which determines the amount by which given inputs can be proportionally reduced. Supposing, if DMU_0's energy consumption performance is efficient in time period t and further in that DMU_0 if the amount of energy already used cannot be reduced with the given value-added, then that $DMU_0$is said to be on the efficient production frontier (EPF). If its energy consumption performance is inefficient and can still produce the given value added after reducing the proper amount of energy, which means $DMU_0$is operating below the EPF[3], then it can reach the EPF after input reduction. Suppose we have a production function in time period $t$as well as period t + 1; the Malmquist productivity index calculation requires two single periods and two mixed period measures (Charnes et al. 1978). From the time period t to t + 1, DMU_0's technical efficiency and the EPF may shift. We adopt the algorithm developed by Fare et al.[4] to calculate the Malmquist production index by considering energy consumption. It can be calculated via the following steps.

(i) Comparing to EPF at time t, by estimating in the model (1).

(ii) Comparing to EPF at time t + 1 by estimating via the following linear program model:

Model (II)

$D_0^{t+1}(x_0^{t+1}, y_0^{t+1}) = Min\theta_{0,}$

s.t $\sum_{j=1}^{n} \lambda_j \, x_j^{t+1} \leq \theta_0 \, x_0^{t+1},$ (10)

$\sum_{j=1}^{n} \lambda_j \, y_j^{t+1} \geq y_0^{t+1},$

$\lambda_j \geq 0, \ \ j = 1, \ldots, n,$

(iii) Comparing to EPF at time t+1, by calculating through the following linear program model:

Model: III

$D_0^{t+1}(x_0^{t}, y_0^{t}) = Min\theta_{0,}$

s.t $\sum_{j=1}^{n} \lambda_j \, x_j^{t+1} \leq \theta_0 \, x_0^{t},$

$\sum_{j=1}^{n} \lambda_j \, y_j^{t+1} \geq y_0^{t},$

$\lambda_j \geq 0, \ \ j = 1, \ldots, n,$ (11)

(iv) Comparing to EPF at time t, by calculating through the following linear program model:

Model: IV

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[3]R. F¨are, S.Grosskopf, and C. A. K. Lovell, *Production Frontiers*, University Press, Cambridge Cambridge, U.K, 1994.

[4]R. F¨are, S.Grosskopf, and C. A. K. Lovell, *Production Frontiers*, University Press, Cambridge Cambridge, U.K, 1994.

$D_0^t(x_0^{t+1}, y_0^{t+1}) = Min\theta_{0,}$

s.t $\sum_{j=1}^{n} \lambda_j \, x_j^t \leq \theta_0 \, x_0^{t+1},$

$\sum_{j=1}^{n} \lambda_j \, y_j^t \geq y_0^{t+1},$ (12)

$\lambda_j \geq 0, \;\; j = 1, \dots., n,$

The above-stated variables and models have been followed to arrive at the below-given results. The results have been formulated in five different tabular formats. And values of the results have been discussed in the next section.

6.4 Results and Discussion

It is clear from (Table-6.1) that in a scattered manner at different periods the manufacturing sectors have experienced effective energy consumption, as the value of $D_0^t(x_0^t, y_0^t)$ is equal to 1. It also shows that these sectors mostly lie on the efficiency frontier of energy consumption as benchmarks. Among the industries, the basic metal had effective energy consumption for the years 2004, 2007 to 2008, 2013, 2016, and 2020, and the manufacture of beverages sector for the periods 2004, 2007, 2011, 2013, 2016, and 2020. Similarly, chemical and chemical products performed energy efficiently in 2004, 2006,2007, 2013, 2018, and 2020, the coke and refined petroleum products experienced energy efficiency during 2010 and 2016, Similarly, the rest of the industries such as chemical, coke, and refined petroleum products, computer and electronic optical products, electrical equipment, fabricated metal products, furniture, leather-related, machinery and equipment, other metallic mineral products, paper & paper products, pharmaceutical medical, rubber plastic products, manufacturing of textiles, tobacco, wearing apparels, wood products, and other products were found to be energy efficient for some years and energy inefficient for some other periods.

Table-6.1: Input-oriented CRS efficiency of sectors from 2001-2021 $D_0^t(x_0^t, y_0^t)$																				
DMU	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
1	0.721	0.602	0.137	1	0.656	0.934	1	1	0.525	0.673	0.916	0.343	1	0.357	0.883	1	0.193	0.888	0.942	1
2	0.696	0.521	0.146	1	0.614	0.912	1	0.727	0.579	0.710	1	0.202	1	0.195	0.922	1	0.253	0.853	0.942	1
3	0.429	0.690	0.148	1	0.683	1	1	0.663	0.496	0.776	0.741	0.371	1	0.150	0.882	0.778	0.226	1	0.441	1
4	0.472	0.476	0.150	0.966	0.802	0.986	0.597	0.413	0.637	1	0.749	0.463	0.995	0.109	0.837	1	0.287	0.934	0.705	0.387
5	0.655	0.614	0.149	0.247	0.720	1	0.538	0.579	0.653	1	0.833	0.467	0.416	0.129	0.889	1	0.187	0.885	0.592	0.178
6	0.681	1	0.172	0.540	1	0.486	0.564	0.512	0.612	0.903	0.749	0.346	0.595	0.117	0.825	0.950	0.348	1	1	0.198
7	0.796	1	0.154	0.474	1	0.473	0.507	0.478	0.744	0.852	0.893	0.483	0.588	0.109	0.785	0.776	0.382	1	1	0.231
8	0.513	0.851	0.175	0.804	1	0.442	0.474	0.903	1	1	0.888	1	0.966	0.114	0.788	0.850	0.400	1	1	0.147
9	0.554	0.658	0.120	1	0.432	0.421	0.426	0.617	0.701	0.880	1	1	0.516	0.132	1	1	0.445	1	0.793	0.217
10	0.727	0.725	0.135	0.723	0.408	0.414	0.451	0.736	0.804	0.866	0.966	0.773	0.608	0.149	0.494	0.901	0.473	1	0.543	0.355
11	0.585	0.962	0.186	0.567	0.400	0.510	0.497	1	1	0.982	0.830	1	0.604	0.156	0.856	0.955	0.443	0.596	0.752	0.279
12	0.523	0.965	0.338	1	0.372	0.538	0.553	0.802	0.901	1	0.689	0.857	0.369	0.145	0.836	0.944	0.466	0.535	0.720	0.110
13	0.537	0.839	0.348	1	0.377	0.685	0.487	0.476	0.985	1	1	0.893	0.434	0.168	0.811	1	0.872	0.376	0.829	0.443
14	0.625	0.564	0.233	0.771	0.446	0.743	0.527	0.846	0.890	0.110	0.824	0.858	0.586	0.186	0.725	0.972	1	0.618	0.848	0.270
15	0.428	1	0.184	0.969	0.456	0.759	0.536	0.655	1	0.102	0.855	0.885	0.770	0.164	0.799	1	0.754	0.627	1	1
16	0.610	1	0.231	0.878	0.624	0.763	0.541	0.881	1	0.111	0.878	0.928	0.520	0.182	1	0.403	0.990	0.620	0.756	0.905
17	0.595	1	0.341	0.842	0.222	0.950	0.547	1	1	0.110	0.841	0.987	0.649	0.194	0.865	0.401	0.885	0.686	0.684	0.404
18	0.519	0.652	0.491	0.631	0.697	0.860	0.479	1	1	0.100	0.952	1	0.488	0.219	1	0.322	0.862	0.683	1	0.602
19	0.563	0.500	1	0.826	0.570	0.766	0.441	0.866	0.887	0.099	1	0.960	0.475	0.260	1	0.252	1	0.611	0.999	0.618
20	0.616	0.302	1	0.889	0.378	0.712	0.425	0.901	0.999	0.136	1	1	0.533	0.272	0.877	0.318	0.870	0.592	1	0.735
21	1	0.398	0.804	1	0.458	0.544	0.453	0.623	0.871	0.135	1	1	0.571	0.261	0.739	0.276	0.947	0.971	0.997	0.672
22	1	0.397	1	1	0.493	0.607	0.547	0.441	0.911	0.174	0.810	0.922	0.767	0.784	0.602	0.203	1	1	1	0.438
23	0.606	0.401	1	0.761	0.448	0.549	1	0.392	0.982	0.222	0.982	1	0.966	1	1	0.350	0.720	0.984	1	0.502

1. Manufacturing of Basic Metal, 2. Beverages, 3.Chemical and Chemical Products, 4. Coke and Refined Petroleum Products, 5.Computer and Electronic Optical products, 6.Electrical Equipment, 7.Fabricated Metal Products except for Machinery and Equipment, 8. Manufacturing of Food Products, 9. Manufacturing of furniture, 10.Manufacturing of leather-related products, 11. Manufacturing of machinery and equipment, 12. Other Non-Metallic Mineral products, 13. Manufacturing of paper and paper products, 14.Pharmaceutical medical, chemical & botanical products, 15. Rubber plastic product, 16. Manufacturing of textiles, 17. Manufacturing of tobacco products, 18. Manufacturing of wearing apparel, 19. Manufacturing of wood and wood products, 20. Other manufacturing, 21. printing and reproduction of media, 22.Publishing Activities, 23. Crop animal production and Hunting related.

The value of the Malmquist index (Table 6.2) measures the energy efficiency change over a period. In other words, it shows the total factor productivity. A value of more than one indicates that the industry is turning more output to a given level of energy input. Which means the decision-making unit is energy efficient. A value less than one indicates a decline in productivity and a value equal to one means the efficiency is stagnant.

For the period 2001-02, the average factor productivity change was 30 percent. However, during this period, the fabricated metal products (except machinery and equipment) resulted in a higher total factor productivity change of 83.3 percent which is above the average level of productivity change. This is due to the extent of technical efficiency change (45.9 percent) and scale efficiency change (25.7 percent). This type of energy efficiency improvement can be seen among DMU (3 to 11, 13 & 15 to 19 for the period 2001-02). The energy efficiency improvement qualitatively and optimally indicates that these industries used less amount of energy input to generate output. The basic industry with a Malmquist Productivity Index value of 0.984 indicates that there is a decline in the energy efficiency by 1.6 percent (1-0.984=0.016*100=1.6 percent) i.e., energy use per unit of output increased. Similarly, for the period 2002-03, we find total factor productivity improvement for DMU such as (4, 12 to 18 & 20 to 23), of which printing and reproduction of media resulted in higher efficiency of 88.9 percent. Similarly, energy efficiency improvement or deterioration can be tracked in subsequent periods. The periods 2005-06 and 2006-07 witnessed a decline in the total factor productivity across different industries whose value was less than one. The period 2008-09 saw energy efficiency improvement among DMU 4, 7, 13 & 20 to 23, the rest of the industries faced more energy per unit of output. For the period 2009 to 2010, the DMU 14 to 23 faced low factor productivity however DMU 1 to 13 witnessed higher factor productivity. In this sense, these units gained energy efficiency. The period 2010-11 indicated that DMU 1 to 13 experienced energy-inefficient outcomes whereas 14 to 23 DMUs saw the energy-efficient outcome. Similar inferences can be drawn from subsequent periods.

Table-6.2: Value of MPI

DMU	01-02	02-03	03-04	04-05	05-06	06-07	07-08	08-09	09-10	10-11	11-12	12-13	13-14	14-15	15-16	16-17	17-18	19-20	20-21
1	0.984	0.797	1.063	0.484	0.520	0.431	1.069	0.435	1.736	0.068	1.041	1.989	0.597	1.000	0.620	0.281	1.128	1.238	0.622
2	0.921	0.88	1.652	0.518	0.625	0.458	1.874	0.81	1.645	0.077	0.624	1.473	0.244	0.488	0.530	0.354	1.103	1.203	1.231
3	1.780	0.706	1.056	0.762	0.497	0.496	1.136	0.606	1.171	0.049	1.289	1.264	0.19	1.001	0.292	0.398	1.806	0.734	1.020
4	1.235	1.073	1.613	1.138	0.238	0.238	1.176	1.363	1.244	0.036	1.663	1.291	0.165	1.278	0.600	0.375	1.273	1.004	0.565
5	1.210	0.801	1.012	1.349	0.149	0.11	1.807	0.973	1.172	0.039	1.423	1.214	0.405	1.838	0.313	0.254	1.140	1.125	0.276
6	1.082	0.542	1.017	1.186	0.039	0.842	1.742	0.909	1.224	0.041	1.376	1.028	0.264	1.224	0.421	0.499	1.195	1.306	0.087
7	1.833	0.473	1.769	1.777	0.058	0.819	1.512	1.329	1.925	0.034	1.461	1.614	0.255	1.684	0.305	0.672	1.014	1.563	0.251
8	1.289	0.665	1.635	1.677	0.045	0.767	1.130	0.846	1.275	0.034	1.155	1.018	0.162	1.669	0.289	0.640	1.709	1.703	0.115
9	1.697	0.567	1.170	0.689	0.426	0.765	1.434	0.662	1.174	0.036	0.112	0.475	0.341	1.688	0.322	0.604	1.272	1.122	0.206
10	1.232	0.655	1.835	0.624	0.441	0.845	1.351	0.472	1.697	0.040	1.635	0.735	0.304	1.386	0.603	0.714	1.761	1.292	0.597
11	1.783	0.674	1.156	0.842	0.558	0.820	1.592	0.221	1.620	0.020	1.050	0.539	0.319	1.531	0.440	0.633	1.053	1.248	0.297
12	1.043	1.199	1.193	0.816	0.634	0.832	1.530	0.547	1.661	0.021	1.965	0.434	0.481	0.029	0.472	0.666	1.636	1.839	0.131
13	1.591	1.448	1.214	0.695	0.782	0.57	1.849	1.025	1.095	0.020	0.742	0.463	0.471	1.893	0.563	1.174	0.524	1.917	0.390
14	0.992	1.451	1.464	1.026	0.731	0.588	1.892	0.527	0.168	1.157	1.166	0.642	0.386	1.009	0.577	1.431	1.447	1.764	0.259
15	1.806	1.296	1.754	0.794	0.729	0.585	1.393	0.635	0.138	1.316	1.235	0.781	0.259	1.073	0.465	1.126	1.959	1.732	0.807
16	1.016	1.535	1.953	1.086	0.535	0.619	1.879	0.390	0.156	1.180	1.518	0.538	0.425	1.054	0.123	1.450	0.868	1.078	1.026
17	1.055	1.030	1.882	0.920	1.448	0.495	1.066	0.398	0.166	1.206	1.332	0.698	0.404	0.687	0.107	1.933	1.874	1.78	0.511
18	1.481	1.182	0.904	1.583	0.541	0.421	0.321	0.253	0.166	1.602	0.188	0.488	0.588	1.884	0.104	1.688	1.080	1.833	0.602
19	1.017	0.678	0.495	1.054	0.589	0.445	1.693	0.380	0.172	1.814	1.624	0.475	0.667	1.095	0.073	0.473	0.755	1.035	0.544
20	0.712	1.575	0.632	0.763	0.906	0.462	1.721	1.018	0.244	1.394	1.113	0.567	0.621	1.202	0.171	1.152	0.814	1.605	0.576
21	0.438	1.889	0.862	0.801	0.52	0.643	1.254	1.177	0.272	1.501	1.155	0.610	0.558	1.470	0.224	1.980	1.870	1.367	0.611
22	0.419	1.263	1.008	0.714	0.539	0.626	1.984	1.808	0.330	0.915	0.688	0.855	1.287	1.086	0.219	0.109	1.722	1.497	0.359
23	0.772	1.505	0.572	0.902	0.537	1.192	0.661	1.028	0.400	0.891	1.538	1.118	1.716	1.588	0.254	1.773	1.389	1.221	0.461

1. Manufacturing of Basic Metal, 2. Beverages, 3.Chemical and Chemical Products, 4. Coke and Refined Petroleum Products, 5.Computer and Electronic Optical products, 6.Electrical Equipment, 7.Fabricated Metal Products except for Machinery and Equipment, 8. Manufacturing of Food Products, 9. Manufacturing of furniture, 10.Manufacturing of leather-related products, 11. Manufacturing of machinery and equipment, 12. Other Non-Metallic Mineral products, 13. Manufacturing of paper and paper products, 14.Pharmaceutical medical, chemical & botanical products, 15. Rubber plastic product, 16. Manufacturing of textiles, 17. Manufacturing of tobacco products, 18. Manufacturing of wearing apparel, 19. Manufacturing of wood and wood products, 20. Other manufacturing, 21. printing and reproduction of media, 22.Publishing Activities, 23. Crop animal production and Hunting related.

According to the data above, some decision-making units have experienced productivity gains. It's also important to note that some decision-making units experienced a significant reduction in productivity during this time. Particularly in the reporting period of 2001-2020, we find that practically all of the decision-making units saw decreased productivity in 2013–14, 2015–16, and 2019–20 due to a lack of change in TEC and EPF. Additionally, the research mentioned above demonstrates that despite these 23 decision-making units' significant changes during the reporting period, the productivity change has not been consistent.

6.5 Conclusion

In this chapter, the energy consumption productivity change for 23 manufacturing sectors in India has been measured throughout the reporting period of 2001-2021 using an input-oriented data envelopment model. The decomposed form of the Malmquist productivity index was utilized and presented: Technical Efficiency Change & Efficient Production Frontier Shift (Appendix-1&2). Technical change is quantified using TEC, and the movement in the frontier of efficient production is shown using EPFS. The value of MPI is demonstrated through TEC and EPF. As a result, the shift in the EPF and the change in technical efficiency dictate the change in productivity.

The findings indicated that eight manufacturing industries, including the production of basic metals, beverages, chemicals, and chemical products, as well as furniture, clothing, wood products, rubber and plastic, and printing and reproducing media, consumed energy effectively for at least more than six of the two decadal periods. This proves the fact that those industries who are optimally utilizing energy are able to increase their productivity. Additionally, it implied that these units are quite close to the benchmarks for energy consumption's efficiency frontier. Coke and refined petroleum products, computer and electronic optical products, electrical equipment, fabricated metal items, and food product manufacturing all showed moderate energy efficiency.

One can infer from the foregoing that the Indian government must implement policies to strengthen industrial energy management, particularly in those manufacturing sectors that consume large amounts of energy inputs with low levels of output and generation of gross industrial value added. This will help to enhance and promote the improvement in the productivity of energy consumption of major industry sectors in India.

6.6 References

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