



Productivity Growth and its Relation with Some Socio-economic Structural Factors: Evidence from Indian Manufacturing Industries

Dr. Paramita Roy Biswas

Assistant Professor, Department of Economics, Victoria Institution (College), 78B, A. P. C. Road,
Kolkata-700009, West Bengal, India, email.id: paramita19@gmail.com

DOI : <https://doi.org/10.5281/zenodo.18897794>

ARTICLE DETAILS

Research Paper

Accepted: 20-02-2026

Published: 10-03-2026

Keywords:

*data envelopment analysis,
manufacturing industry,
non-parametric, total factor
productivity*

ABSTRACT

The study tries to calculate productivity growth of 7 Indian manufacturing industries using three-digit level data, collected from Annual Survey of Industries during 2000-2022. Total Factor Productivity (TFP) growth is estimated by Malmquist Productivity Index (MPI), using non-parametric Data Envelopment Analysis. Decomposition of MPI identifies technical change and technical efficiency change as the prime movers. The average TFP growth observed as 4.79%, among which wood products industry shows the highest (10.06%) and beverage-tobacco industry shows the lowest (0.18%) of TFP growth. Some socio-economic-structural factors are found to be relevant in variation of productivity growth. Large firms play significant role in TFP growth of jute and leather industries. Concentration-ratio has positive impact on TFP growth of food processing, wood products and paper industries. Labour-intensive technology may have positive impact on TFP growth of Food processing, beverages-tobacco and leather industries whereas cotton-textile, jute, wood and paper industries may opt for capital-intensive technology. Faulty management system, erroneous operations may affect TFP growth of paper and leather industries. Skilled labourers can help to increase TFP growth of food processing, paper, leather, cotton-textile, jute and beverage-tobacco industries. The study highlights the



need for formulating industry-specific policies for enhancing TFP growth of these industries.

Introduction

Industry has a major role to play in economic development of a country. Any country which wants to perform in industrial sector needs to enhance cost-competitiveness by fostering Total Factor Productivity (TFP) growth. TFP growth measures the amount of increase in total output which is not accounted for the increase in total inputs and thus measures shift in output due to the shift in the production over time, holding all inputs constant [Abramovitz (1956); Denison (1962, 1967, 1985); Hayami et al. (1979)]. This in turn implies an upward/downward shift in production/cost function, thereby leading to an increase in output. It has been widely acknowledged in the economic literature that industrial growth, no matters how impressive, will not be sustainable without improvement in productivity. Naturally measurement of the rate of TFP changes in manufacturing industries and identifying the factors, which account for productivity changes, is of great interest — both in academic purpose and practical sense.

Going through the literature it is found that Goldar et al. (2023) tries to study the TFP growth in India between 1990 – 2019. The empirical analysis suggests at the economic level a significant portion of variation of aggregate TFP growth is explained by deviation in rainfall, global GDP growth rates, public investment in infrastructure etc. Aneja & Arjun (2021) finds productivity growth of both high technology and medium-high technology industries is increasing over time. High technology industries are driven by technology change and medium-high technology industries are driven by technical efficiency change. Satpathi and Hasan (2021) find a link between TFP growth and export, GDP, employment, showing positive and significant relation. So TFP may be considered as a useful way to mitigate economic recession. Rawat (2017) tries to estimate TFP in Indian manufacturing during 2000-2019. SampathKumar and Pardeep (2016), considering 12 Indian manufacturing sectors during 1981-82 to 2007-08 notices the importance of technical efficiency and finds that production deteriorates in post-reform period. Kumar et al. (2015) developed an analytical framework to test the effect of liberalization on TFP growth of Indian manufacturing industries.

The survey of literature reveals that there is to some extent a dearth of the studies regarding the estimation of TFP growth using non-parametric approach and then highlighting some relevant socio-economic structural factors to explain the variation of TFP growth.



So the novelty of the study points out that

The estimation of the variations of TFP growth of 7 selected Indian manufacturing industries is carried out by using non-parametric approach, using three-digit Annual Survey of Industry (ASI) data for the period 2000 to 2022 as a case study. The second stage regression analysis is performed to explore the relationship between TFP growth with some other socio-economic factors and structural variables, like firm size, capital-labor ratio, non-production employee per production worker, real wage and or changes in wage rate.

Methodology

In this study the rate of productivity growth is measured by the difference in growth rates of output and input quantities respectively. The relevant assumptions are — (i) both inputs and output are freely disposable and the production possibility set is convex, (ii) all input-output combinations, actually observed, are by definition feasible and (iii) variable returns to scale (VRS) prevail. After getting the TFP growth scores of different industries, a second stage regression is sorted to find out the relevant factors that are responsible for the variation in TFP growth. The Detailed methodology is given as Appendix.

Data Description

The study visualizes a single-output four-input production technology for three-digit ASI data of 7 different manufacturing industries of India during 2000 to 2022. Output is measured by the gross value of production. The inputs are capital, labor, fuels and materials. Except labor input (measured by number of workers) all other inputs and output data are in value terms (in Rs. 100 thousands). The nominal values of output and inputs are deflated by appropriate price indexes to obtain real values. Capital stock is estimated by perpetual inventory accumulation method. The selected industries with their abbreviations are as follows: Food Products (FP), Beverages, Tobacco & Related Products (BTRP), Cotton Textiles (CT), Jute, Vegetable Fiber (JVF), Wood & Wood Products (W&P), Paper, Paper Products (P&P), Leather & Leather Products (L&P). These industrial sectors are chosen after analysing their share in GDP, net value added, export activities, employment generation capacity etc.

Empirical Results

MPI is obtained by using computer program DEAP (developed by Tim Coelli). The Malmquist Index summary is calculated for the production units corresponding to each year up to 2022. Table-1 represents the sample averages of MPIs (all MPI averages are arithmetic means) for individual industry group. Because the productivity index in any one year treats the year immediately preceding as the base, the difference between the value of the MPI and unity shows the productivity growth rate (PGR) over the previous year. The sample averages of such annual growth rates are also reported in Table-1.

Table-1: Malmquist Productivity Index and Productivity Growth Rate-by Industry (Annual Averages)

Manufacturing Industry Groups	Malmquist Productivity Index	Productivity Growth Rate
FP	1.035	2.75%
BTRP	1.012	0.18%
CT	1.052	4.54%
JVF	1.035	6.95%
W&P	1.110	10.06%
P&P	1.084	7.59%
L&P	1.012	1.45%
Average value of TFP growth, considering all the industry groups: 4.79%		

Authors Calculation

The disaggregated analysis reveals widespread inter-industrial variation of productivity changes. Average TFP growth, taking all industry groups together, is reported as 4.79%. Among all industry groups, 3 exhibit productivity growth rates above the average value and rest of the groups show the rate below the average.

Table-2 reports the results relating to technical progress (or regress) and suggest that one of the significant factors behind the overall progress or decline in productivity, found in different industry groups is the (average) rate of technical change (i.e. progress or regress). FP industry exhibits technical

progress of 11.92%, the highest among all industry groups followed by JVF industry, experiencing technical progress of around 7% per annum. BTRT and L&P exhibit technical progress of less than 1%.

The fourth column of Table-2 reveals that most of the industries improve in technical efficiency over the years. Interestingly, for L&P and W&P industries negative value of technical efficiency change is apparently suggesting adoption of inefficient technology or incapable management indicating technical regress over the years and lowering down of the production frontier. A comparison between technical efficiency change and scale efficiency change (furnished in columns 4 and 5 of Table-2) reveals that change in technical efficiency has a significant role in variation in TFP growth.

Table-2: Contributions of Technical Change, Technical Efficiency Change & Scale Efficiency Change in TFP growth -by Industry (Annual Averages)

Manufacturing Industry Groups	Level of Technical Change	Rate of Technical Change	Technical Efficiency Change	Scale Efficiency Change
FP	1.119	11.92%	3.19%	0.34%
BTRP	1.001	0.15%	1.02%	0.48%
CT	1.052	5.23%	0.78%	1.05%
JVF	1.071	7.14%	1.46%	0.30%
W&P	1.014	1.44%	0.29%	0.07%
P&P	1.068	6.88%	0.15%	0.04%
L&P	1.009	0.97%	0.15%	0.01%
# The Malmquist Productivity Index(MPI) averages are Arithmetic Means				

To analyze wide variation in productivity growth of different manufacturing industry groups as seen in Table-1, a second stage regression analysis is performed to find out the factors responsible for it taking the average annual productivity growth rate (PGR) as dependent variable.

Analysis of Results

The productivity growth of an industry is captured using TFP index (i.e. MPI), following the non-parametric approach of Data Envelopment Analysis. In this analysis, PGR (as obtained from MPI and



explained earlier) is considered as dependent variable, considering each industry separately. The principal independent variables are as follows:

Firm size (Y/N): Output per factory (firm) (Y/N) and this will give the scale of operation also.

Concentration ratio (CR): CR of a particular industry group captures the effect of market structure on TFP growth. A negative relation between CR and TFP growth is expected by some researchers because competition may lead to cost-consciousness and drive for technological advancement. Others may point out the advantages of big size, secured market and expect a positive association between CR and TFP growth. The conclusion from the empirical literature also varies and does not provide us a single answer [(Katz (1969), Kendrick (1973))]. To compute industrial CR the present paper uses Gini-Hirschman

coefficient, captured by the formula:
$$GH = \sqrt{\frac{n}{\sum_{i=1}^n Y_{it}^2}}$$
, where Y_{it} = market share of i th firm in the industry in period t .

Capital-labor ratio (K/L): The capital-labor ratio, as technological variable, gives an idea about the relative degree of mechanization. Normally, it is expected that there exists positive relationship between K/L and TFP growth.

(Non-production) employees per production worker (NP): It is also a technological variable and is related to the composition of work force. A higher number of employees per worker generally signify a higher degree of bureaucratic control within the firm that can hinder productivity. Besides, recruitment of non-production employees is quite often a response to the political pressure by the party in power to provide employment of its party cadres. These political employees are more likely to hinder productivity. Such a line of reasoning postulated a negative relation between NP and TFP growth. On the other hand, a positive relation between NP and TFP growth indicates that the combination of work force is just right to operate efficiently and to promote TFP growth of different industries.

Real wage (W) and change in real wage rate (LNW or DELW): Both are considered as determinants of TFP growth. If W is sufficiently high for any industry group then skilled workers may be attracted towards that industry and considering skill as a positive determinant of TFP growth, it can be argued that as W increases, through the involvement of skilled workers in production process, productivity can increase. It may also be possible that TFP growth is associated with changes in real wage rate, justifying the inclusion of LNW or DELW in the regression process. The existence of multicollinearity among the explanatory variables is tested. The variables that are multicollinear, not included simultaneously in a



single regression (such as, none of the regressions includes K/L and NP simultaneously). Rather different regressions are tried out taking into account different combinations of explanatory variables. Those results, with the best fit are reported. Natural consequence of this approach is that not all the explanatory variables appear in every regression equation.

The results of regression analysis are presented in Table-3 and yield the following observations.

Table-3: Determinants of Average* Productivity Growth in Indian Industries

(Dependent Variable: Productivity Growth Rate (PGR))

Manufacturing Industry Groups	Y/N	CR	K/L	NP	W	LNW	DELW	R ²
FP		3.37 ^b (1.90)	-4.90 ^b (-1.28)		2.81 ^b (2.05)			0.72
BTRP	-2.01 ^a (-0.13)		-3.12 ^b (-0.58)				2.59 ^a (2.12)	0.81
BTRP		-0.70 ^b (-0.79)	-17.89 ^b (-1.82)				2.93 ^b (2.21)	0.77
CT			29.2 ^b (2.32)			2.62 ^a (1.96)		0.86
JVF	3.14 ^b (1.22)		14.69 ^b (1.65)			2.98 ^b (1.04)		0.69
W&P		2.97 ^b (1.81)	33.12 ^b (1.87)				-2.92 ^b (-3.40)	0.74
P&P		3.82 ^b (1.72)	21.90 ^b (4.07)				1.81 ^a (7.23)	0.62
P&P		5.31 ^b (1.90)		-10.28 ^b (-1.41)	1.92 ^a (4.81)			0.78
L&P	2.78 ^b (2.01)		-15.62 ^b (-0.78)	-9.65 ^b (-1.41)	1.84 ^a (4.87)			0.87
L&P	2.62 ^a		-31.29 ^b			-1.98 ^a		0.81



	(1.61)		(-1.98)			(-2.35)		
--	--------	--	---------	--	--	---------	--	--

Averages are obtained from the estimates of PGR calculated at three-digit disaggregated level.

Each estimated equation includes a constant term.

Figures in parentheses are t-ratios. ^a- Significant at 1%, ^b- Significant at 5%,

The coefficient of firm size (Y/N) is positive and statistically significant for JVF, L&P industries implying that increase in firm size may foster TFP growth may be due to economies of scale, better financial access. BTRP shows negative impact of firm size on TFP growth may imply smaller firms are more productive due to better management system, skilled labourers.

The coefficient of concentration ratio (CR) is positive and statistically significant for FP, W&P and P&P signifying the advantages of big size, clustering of firms over the years, lead to enhance TFP growth, whereas, CR has no significant impact on TFP growth of BTRP.

The coefficient of capital-labor ratio (K/L) is positive for CT, JVF, W&P, P&P industries implying reduction in non-tariff barriers and effective rate of protection, there is a decrease in relative cost of imported capital goods; as a result, there is a rise in capital-labor ratio supporting the technological progress, which in turn, facilitates TFP growth of respective industry groups. Negative impact of K/L on FP, BTRP, CT and L&P industries perhaps lead them to think about adopting labour intensive technology.

The coefficient of (non-production) employees per production worker (NP) is negative and statistically significant for P&P and L&P industries. It can be argued that reduction of internal bureaucracy by lowering the number of (non-production) employees can be resulted to increase in TFP growth.

Increase in real wage (W) have a favorable effect on TFP growth of FP, P&P and L&P industries implying inclusion of better skilled labourers induces higher TFP growth. The coefficient of change in real wage rate (LNW or DELW) is positive and statistically significant for BTRP, CT, JVF and P&P industries. It may be noted that with gradual increase in wage rate, skilled workers may be hired thus enhancing the TFP growth. On the other hand, the coefficient of LNW or DELW is negative and significant for W&P and L&P industries. **Conclusion**

The study incorporates non-parametric approach of DEA to measure TFP growth, which has the following advantage that no assumption is required regarding functional relationship between inputs and



output. This study aims to highlight TFP growth of 7 Indian manufacturing industries and the relevant factors for the variations in TFP growth. The average TFP growth observed as 4.79% considering all 7 industries, among which W&P industry shows the highest (10.06%) and BTRP industry shows the lowest (0.18%) TFP growth. Technical progress (regress) and increase (decrease) in technical efficiency over the years play vital role behind the overall change (progress or decline) in productivity.

Large firms play significant role in TFP growth of JVF, L&P industries. Concentration ratio has positive impact on TFP growth of FP, W&P and P&P industries. Labour-intensive technology may increase TFP growth of FP, BTRP and L&P industries whereas capital-intensive technology may raise the TFP growth of CT, JVF, W&P and P&P industries. Faulty management system, erroneous operation may affect TFP growth of P&P and L&P industries. Increase in wage rate and change in wage rate (wage differential) has positive impact on TFP growth of FP, P&P, L&P, CT, JVF, BTRP industries implying skilled labourers can help to increase TFP growth of these industries.

To sum up, the study highlights the need for formulating industry-specific policies for enhancing TFP growth of these 7 Indian manufacturing industries, keeping in mind the degree of responsiveness of the socio-economic, structural factors in explaining TFP growth of different manufacturing industries over the years.

Appendix

Consider, for simplicity, a single input – single output industry consists of n firms. Let x_k^t and y_k^t represent the input and output quantities of firm k at time t. The average productivity of this firm at time t

$$\text{is } AP_k^t = \frac{y_k^t}{x_k^t} \quad (1)$$

Thus, a productivity index for this firm at time t+1, with period t treated as the base, will be

$$\Pi_{k(t+1)} = \frac{AP_k^{t+1}}{AP_k^t} = \frac{\frac{y_k^{t+1}}{x_k^{t+1}}}{\frac{y_k^t}{x_k^t}} \quad (2)$$

which does not in any way depend on the assumptions about returns to scale. In order to identify the sources of productivity change, however, a bench-mark technology is needed, where returns to scale assumption becomes important.

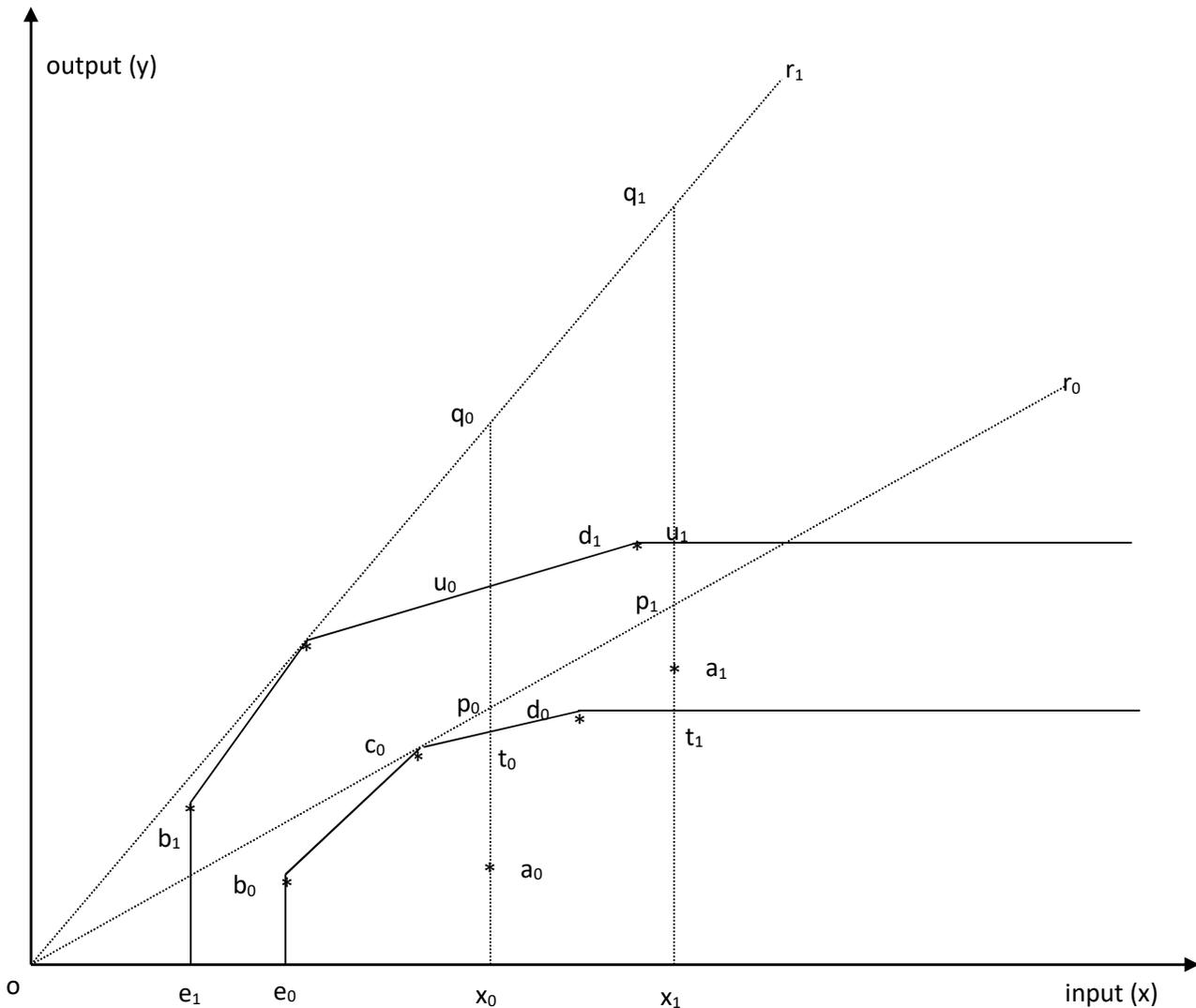


According to Varian (1984), the free disposal convex hull of observed input-output vectors provides an inner-approximation to the true underlying production possibility set, if the above-mentioned assumptions [(i) & (ii)] hold good.

Consider an industry consisting of four firms: a, b, c and d. Following Figure-1, a_0, b_0, c_0 and d_0 show the observed input-output levels of the respective firms in period 0. Similarly, points a_1 through d_1 show their input-output levels in period 1. Firm 'a' uses input ox_0 to produce output a_0x_0 in period 0 and input ox_1 to produce output a_1x_1 in period 1.

Thus, the productivity index for firm 'a' in period 1 is

$$\Pi_{a1} = \frac{a_1x_1/ox_1}{a_0x_0/ox_0} \tag{3}$$



By convexity, all the points in the convex hull of the points a_0, b_0, c_0 and d_0 (i.e., the convex combinations of these points) represent feasible input-output combinations in period 0.

The free disposal convex hull is the set of points bounded by the horizontal axis and the broken line $e_0 b_0 c_0 d_0$ – extension. Under VRS, all points in this region represent feasible input-output combinations in period 0, although under Constant returns to scale (CRS) all radial expansion and (non-negative) contraction of feasible input-output bundles are also feasible, thus the CRS production possibility set in period 0 is the cone formed by the horizontal axis and the ray or_0 through the point c_0 .

The VRS frontier in period 1 is the broken line $e_1 b_1 c_1 d_1$ - extension and the CRS frontier is the ray or_1 through the point c_1 . Define the production possibility set as

$$S^t = \{(x, y) : y \text{ can be produced from } x \in \text{period } t\} \tag{4}$$

The output distance function is

$$D^t(x, y) = \min \theta : \left(x, \frac{1}{\theta} y \right) \in S^t \tag{5}$$

In period 0, the maximum producible output from input ox_0 is $t_0 x_0$ under the VRS assumption. Thus the distance functions are

$$D_V^0(x_0, y_0) = \frac{a_0 x_0}{t_0 x_0} \quad \text{and} \quad D_V^0(x_1, y_1) = \frac{a_1 x_1}{t_1 x_1}, \text{ in period 0}$$

The productivity index for firm ‘a’ is

$$\Pi_{a0} = \frac{\frac{a_1 x_1 / ox_1}{a_0 x_0 / ox_0}}{\frac{p_1 x_1 / ox_1}{p_0 x_0 / ox_0}} = \frac{D_c^0(x_1, y_1)}{D_c^0(x_0, y_0)} \tag{6}$$

$$\text{Analogously, } \Pi_{a1} = \frac{\frac{a_1 x_1 / ox_1}{a_0 x_0 / ox_0}}{\frac{D_c^1(x_1, y_1)}{D_c^1(x_0, y_0)}} \tag{7}$$

According to Färe, Grosskopf, Norris and Zhang (FGNZ, 1994) for any reference technology; the distance functions can be calculated. The productivity index is given by the ratio of the CRS distance functions even if the technology was not characterized by CRS. With explicit assumption of VRS, comparing CRS and VRS frontiers in period 0, one gets both t_0 and t_1 are points on the production frontier, (both are technically efficient), and the average productivity at t_0 is higher than that of t_1 . The point of highest average productivity along the VRS frontier in period 0 is c_0 , whereas along the CRS frontier, that remains constant. The point of highest average productivity along the VRS frontier is called the Most Productive Scale Size (MPSS), according to Bankar, Charnes and Cooper (1984). At the MPSS, CRS and VRS frontiers coincide. Notably, the average productivity at MPSS of the VRS frontier (point c_0) is equal to the constant average productivity at any point on the CRS frontier (say, p_0 or p_1). The scale efficiency at any point on the frontier is measured by the ratio of the average productivity at that point to the average productivity at MPSS.

$$\text{Thus, } SE^0(x_0, y_0) = \frac{AP(t_0)}{AP(c_0)} = \frac{t_0 x_0}{p_0 x_0} = \frac{D_c^0(x_0, y_0)}{D_v^0(x_0, y_0)} \quad (8)$$

$$\text{Also, } SE^0(x_1, y_1) = \frac{AP(t_1)}{AP(c_0)} = \frac{D_c^0(x_1, y_1)}{D_v^0(x_1, y_1)} \quad (9)$$

Now equation (6) can be written as

$$\Pi_{a0} = \frac{D_v^0(x_1, y_1) \cdot \frac{D_c^0(x_1, y_1)}{D_v^0(x_1, y_1)}}{D_v^0(x_0, y_0) \cdot \frac{D_c^0(x_0, y_0)}{D_v^0(x_0, y_0)}} = \frac{D_v^0(x_1, y_1)}{D_v^0(x_0, y_0)} \cdot \frac{SE^0(x_1, y_1)}{SE^0(x_0, y_0)} \quad (10)$$

$$\text{In a perfectly analogous manner, } \Pi_{a1} = \frac{D_v^1(x_1, y_1)}{D_v^1(x_0, y_0)} \cdot \frac{SE^1(x_1, y_1)}{SE^1(x_0, y_0)} \quad (11)$$

Now, the MPI can be decomposed, as done by Ray and Desli (1997), in the following manner. The expression is, $\Pi_a = (\Pi_{a0} \cdot \Pi_{a1})^{\frac{1}{2}}$

$$\begin{aligned}
&= \left[\frac{D_v^0(x_1, y_1) \cdot SE^0(x_1, y_1)}{D_v^0(x_0, y_0) \cdot SE^0(x_0, y_0)} \times \frac{D_v^1(x_1, y_1) \cdot SE^1(x_1, y_1)}{D_v^1(x_0, y_0) \cdot SE^1(x_0, y_0)} \right]^{\frac{1}{2}} \\
&= \left[\frac{D_v^0(x_1, y_1)}{D_v^0(x_0, y_0)} \cdot \frac{D_v^1(x_1, y_1)}{D_v^1(x_0, y_0)} \right]^{\frac{1}{2}} \times \left[\frac{SE^0(x_1, y_1) \cdot SE^1(x_1, y_1)}{SE^0(x_0, y_0) \cdot SE^1(x_0, y_0)} \right]^{\frac{1}{2}} \\
&= \frac{D_v^1(x_1, y_1)}{D_v^0(x_0, y_0)} \times \left[\frac{D_v^0(x_0, y_0)}{D_v^1(x_0, y_0)} \cdot \frac{D_v^0(x_1, y_1)}{D_v^1(x_1, y_1)} \right]^{\frac{1}{2}} \times \left[\frac{SE^0(x_1, y_1) \cdot SE^1(x_1, y_1)}{SE^0(x_0, y_0) \cdot SE^1(x_0, y_0)} \right]^{\frac{1}{2}} \quad (12)
\end{aligned}$$

$$= \text{peffch} \cdot \text{techch} \cdot \text{sch}$$

where $\text{peffch} = \frac{D_v^1(x_1, y_1)}{D_v^0(x_0, y_0)}$ measures pure technical efficiency change,

$\text{sch} = \left[\frac{SE^0(x_1, y_1) \cdot SE^1(x_1, y_1)}{SE^0(x_0, y_0) \cdot SE^1(x_0, y_0)} \right]^{\frac{1}{2}}$ measures change in scale efficiency, and

$\text{techch} = \left[\frac{D_v^0(x_0, y_0) \cdot D_v^0(x_1, y_1)}{D_v^1(x_0, y_0) \cdot D_v^1(x_1, y_1)} \right]^{\frac{1}{2}}$ measures technical change, which is the geometric mean of the shift in the production function at x_0 and x_1 .

FGNZ (1994) showed a similar decomposition. However, as pointed out by Ray and Desli (1997), there exists some inconsistency in their method of analysis. The technical change factor, according to FGNZ (1994), is the geometric mean of the shift in pseudo production function and not of actual production function.

Non-parametric Methodology

The decomposition of MPI into technical efficiency change, technical change and scale efficiency change can be applied in practical sense if the reference technology set is constructed from sample data in the following way — Let, y'_j and x'_j represent the output and input vectors respectively of firm j ($j=1, 2, 3$



...N) in period t. Following Varian (1984), an inner approximation to the underlying production possibility set in period t will be

$$S^t = \{(x, y) : \sum_{j=1}^N \lambda_j x_j^t \leq x; \sum_{j=1}^N \lambda_j y_j^t \geq y; \sum \lambda_j = 1; \lambda_j \geq 0 (j=1,2,3,\dots,N)\}$$

It is to be noted here that, by assumption, any observed input-output bundle (x_t^j, y_t^j) is feasible in period

t. By the convexity assumption, any input-output pair (\bar{x}, \bar{y}) satisfying

$$\bar{x} = \sum_{j=1}^N \lambda_j x_j^t, \bar{y} = \sum_{j=1}^N \lambda_j y_j^t, \sum_{j=1}^N \lambda_j = 1, \lambda_j \geq 0, (j=1,2,3,\dots,N)$$

is also feasible, and by the free disposability assumption, any $x \geq \bar{x}$ corresponds \bar{y} .

Hence, x can also produce y if $y \leq \bar{y}$.

Therefore, the output oriented distance function under VRS is obtained as

$$D_V^t(x_k^i, y_k^i) = \frac{1}{\Phi^*}, \text{ where } \Phi^* = \max \Phi$$

$$\text{subject to } \sum_{j=1}^N \lambda_j y_t^j \geq \Phi y_k^t; \sum_{j=1}^N \lambda_j x_t^j \leq x_k^t; \sum_{j=1}^N \lambda_j = 1; \lambda_j \geq 0, (j=1,2,3,\dots,N)$$

The own-period distance functions can be found for $t=k$, while $t \neq k$ will define the cross-period distance function.

References

- Abramovitz, M. (1956). Resources and Output Trends in United States since 1870, *American Economic Review*, 46(2), pp. 5-23.
- Ahluwalia, I. J. (1991). *Productivity Growth in Indian Manufacturing Industry*, Oxford University Press, New Delhi.
- Aneja R., G. Arjun. (2021). Estimating Components of Productivity Growth of Indian High and Medium-high Technology Industries: A non-parametric Approach, *Social Sciences & Humanities Open*, Vol. 4(1)



- Central Statistical Organization (Kolkata): *Annual Survey of Industries-Summary Results for Factory Sector: Different Issues*.
- Denison, E. F. (1967). *Why Growth Rates Differ – Post War Experience in Nine Western Countries*, The Brookings Institution, Washington DC.
- Denison, E. F. (1985). *Trends in American Economic Growth: 1929-1982*, The Brookings Institution, Washington DC.
- Goldar B. et al. (2023). Determinants of TFP growth in India, *Theoretical Economics Letter*, 13(3)
- Hayami, Y., W. R. Vemon and H. M. Southword (1979). *Agricultural Growth in Japan, Taiwan, Korea and Philippines*, The University Press of Hawaii, Honolulu.
- Katz, J. M. (1969). *Production Function, Foreign Investment and Growth*, North-Holland Publishing Company.
- Kendrick, J. W. (1956). Productivity Trends: Capital and Labor, *Review of Economics and Statistics*, 38(3), pp. 248-257.
- Kumar S., S. K. Baliyan, S. Kumar & K. Baliyan (2015). Total Factor Productivity Growth of Indian Manufacturing: An Analysis after Liberalization, *Asian Journal of Research in Social Sciences and Humanities*, 5(5), pp. 38-51
- Rawat P. (2017). Total Factor Productivity in Indian Manufacturing (2000-2019): A KLEM Approach, *Working Paper*, Madras School of Economics
- Ray, S.C. (1997). Regional Variation in Productivity Growth in Indian Manufacturing: A Non-parametric Analysis, *Journal of Quantitative Economics*, 13(1), pp. 74-93.
- Ray, S.C. and E. Desli (1997). Productivity Growth, Technical Progress and Efficiency Changes in Industrialized Countries: Comment, *American Economic Review*, 87(5), pp. 1033-39.
- SampathKumar T. and V. Pradeep (2016). Estimating Total Factor Productivity and its Components – Evidence from Manufacturing Sector of Tamilnadu, *Indian Journal of Applied Research*, 16(8)
- Satpathi S. and Md. R Hasan (2021). Productivity Growth in the Indian Manufacturing Sector: A Way of Mitigating Recession, Mihir Kumar Pal (ed.) *Productivity Growth in the Manufacturing Sector: Mitigating Global Recession*
- Varien, H. (1984). The Non-parametric Approach to Production Analysis, *Economica*, 52, pp. 579-99.