International Journal of Applied Economics, Finance and Accounting
ISSN 2577-767X
Vol. 16, No. 2, pp. 248-263
2023
DOI: 10.33094/ijaefa.v16i2.969

An assessment of efficiency and productivity analysis of manufacturing industries in Bangladesh

Omotara Adeeko[1]
Olajide Idris Sanusi[2]
Mosab I. Tabash[3*]

[1]*Department of Business Administration and Economics, Massachusetts College of Liberal Arts, MA, 01247, USA.*
Email: ooa18@pitt.edu
[2]*Department of Innovation in Govt. & Society, CBE, United Arab Emirates University, Al-Ain, United Arab Emirates.*
Email: idrissanusy@uaeu.ac.ae
[3]*College of Business, Al Ain University, Al-Ain, United Arab Emirates.*
Email: mosab.tabash@aau.ac.ae

Keywords:
Bangladesh
Convergence
Manufacturing industries
Stochastic frontier
Technical efficiency
Total factor productivity.

JEL Classification:
C23; D24; O14; O47.

Received: *22 February 2023*
Revised: *19 April 2023*
Accepted: *4 May 2023*
Published: *12 May 2023*
(Corresponding Author)*

Abstract

This empirical study employs stochastic frontier analysis to evaluate the Total Factor Productivity (TFP) growth and technical efficiencies of the manufacturing sector in Bangladesh. The study draws data from five rounds of surveys conducted between 1982/83 and 2012. TFP growth is decomposed into efficiency growth, scale component, and technological progress to identify the sources of growth. The technical efficiency of the manufacturing industries in Bangladesh averages 80%, with export-oriented industries exhibiting higher efficiency than non-export industries. Small-scale industries show higher TFP growth than medium- and large-scale industries. The study estimates the TFP growth in Bangladesh's manufacturing sector at approximately 5.5% during the review period, with technological progress being a key driver of growth. The results also indicate TFP growth convergence over time among the manufacturing industries in Bangladesh. The study highlights the potential for productivity improvement and income growth in Bangladesh's manufacturing sector. Further investigation into TFP and efficiency is necessary to achieve this potential fully. The study's findings suggest that policymakers in Bangladesh should focus on promoting technological progress and improving the efficiency of manufacturing industries, especially in medium- and large-scale industries. Moreover, the government should develop policies that support export-oriented industries to improve their efficiency.

Funding: This study received no specific financial support.
Competing Interests: The authors declare that they have no competing interests.

1. Introduction

Bangladesh has been experiencing an annual growth increase of approximately 7.4%, making it one of the fastest growing economies in the world, and the manufacturing sector is a major contributor to this increase. Manufacturing share to GDP has been increasing over the last two decades, contributing approximately 14% in 2000 to approximately 19% in 2019 (World Bank, 2019). Bangladesh aims to become a middle-income country by 2021, as part of its growth goal. The Seventh Five Year Plan, aligned with Vision 2021, has paid significant attention to the manufacturing sector, and the plan acknowledges the significance of the manufacturing sector in helping to increase growth in the economy. The success of this sector is largely attributed to factors such as low labor costs, favourable government policies as mentioned above, and increased foreign investment. However, to sustain this growth and maintain a competitive advantage, it is essential to understand the drivers of productivity in the manufacturing industry. One approach to measuring productivity is through Total Factor Productivity (TFP) growth, which captures the efficiency of the use of inputs in production processes. Another approach is through the measurement of Technical Efficiency (TE), which measures the ability of firms to produce the maximum output from given inputs. Both TFP and TE are commonly analyzed using Stochastic

Frontier Analysis (SFA), a method that considers the uncertainty and inefficiencies that exist in real-world production processes.

The projection from the Seventh Five Year Plan shows that the manufacturing sector will be a greater contributor to economic growth than the agricultural and service sectors, and its contribution will continue on an upward path. The projection shows an increase in the manufacturing sector's contribution to gross domestic product (GDP) to 21% by the end of 2020. Additionally, the manufacturing sector will help in the creation of jobs for the newly employed and underemployed labor force, and its share of employment will range from 15 percent to 20 percent. Considering the targets of Vision 2021, it is vital to seriously consider the manufacturing sector, which is set to increase employment, productivity, and the per capita income of the country, which will help in reducing poverty in Bangladesh.

This research aims to evaluate the technological progress, scale economy, cost efficiency, and total factor productivity of the manufacturing sector in Bangladesh over a period of three decades, with a particular focus on 2005/2006 and 2012. Efficiency in the Bangladeshi manufacturing sector has been examined previously. Samad and Patwary (2002) estimated the mean technical efficiency of the Bangladesh manufacturing industries to be 0.85, which suggests that the manufacturing sector has the potential to produce 85% of its maximum output. They also showed that output elasticities for capital and raw materials have been increasing, suggesting that there has been a transformation in the manufacturing sector. Additionally, using data envelopment analysis (DEA), Hassan, Isik, and Mamun (2010) examined firms in Bangladesh for the periods 1993 and 1998 and found that most of the manufacturing firms experienced a positive total factor productivity growth, with a mean of 29% during the five-year period. The study also revealed that export-oriented firms outperformed import-oriented firms in technical efficiency.

Several studies have focused on evaluating the efficiency of manufacturing industries (Cainelli, Ganau, & Giunta, 2018; Chen, Liu, & Zhu, 2022; Gupta, Kumar, & Wasan, 2021; Sony & Naik, 2020; Wang, Wang, & Yao, 2021) with less focus on TFP growth in the manufacturing sector as a whole. Other studies have been carried out showing the stages of productivity change at the local and regional levels (Kalkuhl & Wenz, 2020; Miao, Baležentis, Shao, & Chang, 2019; Szalavetz, 2019), while few studies have been carried out on variations in productivity growth at the national level (Autor & Salomons, 2018; Sheng, Tian, Qiao, & Peng, 2020). Most researchers study changes in productivity using the Cobb–Douglass function, Tornquist index, Solow index, and Hicks-Moorsteen DEA-Malmquist index, while a more specific decomposition approach is lacking in evaluating productivity change, especially for the manufacturing sector in Bangladesh.

Hence, we address the following questions using empirical application based on a sample of the manufacturing industries in Bangladesh. We assess productivity changes at different levels of the manufacturing sector by the decomposition method using the translog function of stochastic frontier analysis to calculate efficiency. In this regard, this research explicitly evaluates efficiency and factors that contribute to productivity changes in Bangladesh's manufacturing industries by applying the technique of total factor productivity (TFP) decomposition. The TFP decomposition evaluates the scale component, technological progress, and efficiency growth to observe efficiency and growth at different levels. To the best of our knowledge, this research is the first to carry out this study for the Bangladesh manufacturing sector using the decomposition method for TFP growth, thereby observing the result that emanates from a different perspective.

This study aims to contribute to the existing literature on productivity growth in the manufacturing industry in Bangladesh by examining TFP growth, TE, and their determinants by employing the decomposition method, which allows us to not only estimate the growth of TFP but also detect the source of the growth. This method also allows us to relax the supposition that inputs are allocated efficiently, which is more conceivable in the real world. In doing this, the translog production function is evaluated for manufacturing industries for 2005/2006 and 2012.

The result indicates that the mean cost efficiency for this period is 80%. Total factor productivity growth was, on average, 5.5% for the period in view. Technological progress is shown to surpass efficiency changes and scale components for industries. Therefore, technological progress has contributed significantly to TFP growth more than the changes in scale component and efficiency. The average technical efficiency was the same for large and medium-sized industries. Furthermore, our result shows that only large industries experienced economies of scale, with small and medium industries having diseconomies of scale; meanwhile, technological progress (TP) is present irrespective of the size of the industry.

The findings of this study indicate that, on average, export-oriented industries exhibit higher technical efficiency compared to non-export-oriented industries. The higher TFP growth observed in the export sector can be attributed to the benefits of economies of scale and technological progress, with the latter playing a crucial role. In contrast, the TFP growth of non-export industries is driven by both technological progress and efficiency changes, with technological progress being a significant contributing factor.

This research is structured to provide a comprehensive examination of the study. In Section 2, a literature review is conducted to provide context and background information. The methodology and data used in this study are described in detail in Sections 3 and 4, respectively. The results of the analysis are presented in Section 5, followed by a conclusion in Section 6 that summarizes the findings and implications of this study.

2. Literature Review

The concept of using Stochastic Frontier Analysis (SFA) to measure efficiency among manufacturing firms was first introduced through the pioneering work of Aigner, Lovell, and Schmidt (1977). Their study analyzed the metals industry in the United States across 28 states for the years 1957-1958. Meeusen and Den (1977) similarly applied SFA to the French Census Manufacturing data for 1962, finding that sectoral efficiency ranges from 0.70% to 0.94%. These early works established the foundation for using SFA as a tool to estimate efficiency in the manufacturing sector. A number of other studies that followed suit in utilizing SFA with panel data include key contributions of Battese and Coelli (1988); Kumbhakar (1990); Kirjavainen (2012); Lai and Kumbhakar (2018); Tsukamoto (2019); Cabrera-Suárez and Pérez-Rodríguez (2021) and Subal C Kumbhakar and Tsionas (2021). These studies have further expanded the application of SFA in the estimation of efficiency in the manufacturing sector.

SFA has not only been applied to the manufacturing sector, but also to other industries such as agriculture, services, and finance. Studies in the agriculture sector include Mehmood, Rong, Bashir, and Arshad (2018); Benedetti, Branca, and Zucaro (2019); Auci and Vignani (2020), and Bibi and Khan (2021). The application of SFA in the financial sector has been explored in studies by Bhaumik, Das, and Kumbhakar (2012); Gupta, Raychaudhuri, and Haldar (2018); Sadalia, Kautsar, Irawati, and Muda (2018) and Liu (2019). In the manufacturing sector, the application of SFA has been the subject of recent empirical studies, such as Kaynak and PagÁn (2003) who evaluated technical efficiency in U.S. manufacturing industries and found that on average, the industries were operating at approximately 85% of their capacity. Kim and Han (2001) investigated the sources of efficiency in manufacturing industries in Korea, finding that productivity growth was driven by technical progress. They also found that changes in technical efficiency had a substantial positive impact, while allocative efficiency had a negative impact. In contrast, Mokhtarul Wadud (2004) conducted a study on the efficiency of clothing and textile firms in Australia, and estimated the mean technical efficiency to be between 30% and 70%. Bhaumik et al. (2012) similarly examined the efficiency of clothing and textile firms in Spain and Poland, concluding that, on average, the efficiency score of both countries was approximately 86%. These studies highlight the diversity of results that can be obtained when utilizing SFA to estimate efficiency in different manufacturing sectors and countries.

Few studies have explored the efficiency of the manufacturing sector in Bangladesh using different methods. Baten, Kamil, and Fatama (2009) utilized a time-varying stochastic frontier and the truncated normal distribution to examine the Bangladeshi manufacturing sector, finding that the mean technical efficiency was 0.339 and 0.356, indicating that firms could increase their output by 66 and 64 percent, respectively, given the same inputs and technology. Samad and Patwary (2002) employed panel data from 13 years (1981-1994) for 31 major industries and estimated the mean technical efficiency of the manufacturing sector in Bangladesh to be 0.85, signifying that its potential output is 85%. Baten, Rana, Das, and Khaleque (2006) estimated the mean efficiencies according to the truncated and half normal distributions to be 0.4022 and 0.5557, respectively, for the period 1981/82-1999/2000. In a study testing the Cobb-Douglas production function for six major industries, including Garments, Textiles, Food & Food Processing, Leather & Leather Products, Electronics, and Chemicals & Pharmaceuticals, Husain and Islam (2016) found evidence of increasing returns to scale in the manufacturing sector, which could support employment and economic growth. These studies provide a foundation for exploring the efficiency of the manufacturing sector in Bangladesh through SFA analysis.

Our research delves deeper into the exploration of manufacturing industries in Bangladesh by estimating both technical efficiency and total factor productivity growth through the use of a decomposition approach. This method enables us to measure TFP growth and identify its sources, as we estimate the translog production frontier for the time period of 2005/2006 to 2012. The uniqueness of this approach also accommodates the real-world scenario where efficient utilization of inputs may not always be assumed.

The estimation of productivity has been a topic of discussion among the Asian economies. This can be achieved through various methods, including the neo-classical approach, which calculates the total factor productivity (TFP) growth as the growth of output that cannot be attributed to the inputs in the production process. Another method is the decomposition approach, where TFP growth is divided into three components: technological progress, economies of scale, and changes in technical efficiency. The analysis of TFP growth in Asian economies has been extensively studied. Kim and Han (2001) used a stochastic frontier production function and decomposition approach to demonstrate that the main driver of productivity growth in Korean manufacturing firms was technical progress. Chen et al. employed Malmquist and Hicks-Moorsteen indices to measure changes in productivity in China's high-tech industries. Oguchi, Amdzah, Bakar, Abidin, and Shafii (2002) utilized growth accounting to analyse TFP growth in both domestic and foreign companies in the Malaysian manufacturing sector, and found that TFP growth was similar for both. A similar study was conducted by Koh, Rahman, and Tan (2002) for the manufacturing industries in Singapore. Margono and Sharma (2006) applied TFP decomposition to examine the growth of total factor productivity in the chemical, textile, metal, and food products industries in Indonesia. The results showed that the textile sector had a mean TFP growth of -0.26% between 1993 and 2000, while the food sector's TFP growth was -2.73%, and the metal products sector's TFP growth was -1.65%. The only sector with positive growth was the chemical sector, which recorded a TFP growth of 0.5%.

Over the past two decades, various techniques have been utilized to calculate the TFP growth of Bangladeshi manufacturing industries. Hassan et al. (2010) conducted a study using data envelopment analysis (DEA) on 82 firms over two time periods (1993 and 1998) and found that most of the firms in the Bangladeshi manufacturing sector saw positive TFP growth, averaging 29% over a five-year period. Fernandes (2008) used the method proposed by Olley and Pakes (1992) to determine TFP measures and found the total productivity growth in five industries (food, leather/footwear, pharmaceuticals, ready-made garments, textiles) in Bangladeshi manufacturing firms to be 58% from a firm survey between 1999 and 2003. Similarly, Samad and Patwary (2002) utilized panel data to determine the mean technical efficiency for the Bangladeshi manufacturing sectors. Additionally, Baten et al. (2009) used a time-varying stochastic frontier and the truncated normal distribution to study the Bangladeshi manufacturing industries and estimated the mean technical efficiency to be 0.339 and 0.356.

3. Methodology

To estimate efficiency, we use the stochastic production function for a firm, which is expressed as follows:

$$y_{it} = f(x_{it}, t) + \exp(-u_{it})$$

Where y_{it} is the output of the ith firm (i = 1..., N) in the tth time period (t = 1...., T); f (·) is the production frontier; x is an input vector; the error term ε_{it} comprises two components: a random component and the inefficiency part $u_{it;}$ thus, $\varepsilon_{it} = v_{it} - u_{it}$. The former is distributed as a two-sided normal distribution with mean zero and variance, σ_v^2, $\boldsymbol{N}(0, \sigma_v^2)$, and the latter is assumed to be distributed as a truncated normal. To allow for efficiency changes over time, Battese and Coelli (1992) extended the time invariant efficiency parameter to the time variant. For time-varying cost efficiency, u_{it} is expressed as a function of parameters associated with time. That is, $u_{it} = \eta_t u_i$, where $\eta_t = \exp[-\delta(t-T)]$ and δ is a parameter that represents the rate of change in technical inefficiency. A positive value (δ > 0) is associated with the improvement of firms' technical efficiency over time; if δ < 0, technical efficiency decreases at an increasing rate, and if δ= 0, technical efficiency remains unchanged.

Following Battese and Coelli (1992) technical efficiency is estimated using the minimum mean-square-error predictor,

$$\begin{aligned} TE_{it} &= E[\exp(-u_{it}|\varepsilon_i) \\ &= \left[\frac{1-\Phi(\eta_{it}\sigma_* - (\mu_{*i}/\sigma_*))}{1-\Phi(-(\mu_{xi}/\sigma_x))}\right] exp\left\{-\eta_t\mu_{*i} + \frac{1}{2}\eta_t^2\sigma_*^2\right\} \end{aligned}$$

Where

$$\mu_{*i} = -\frac{\mu\sigma_v^2 - \eta'\epsilon_i\sigma_u^2}{\sigma_v^2 + \eta'\eta\sigma_u^2},$$

$$\sigma_* = \frac{\sigma_v^2\sigma_u^2}{\sigma_v^2 + \eta'\eta\sigma_u^2}$$

η' = $(\eta_1, \eta_2, \eta_3, \ldots, \eta_T)$, and $\Phi(\bullet)$ is a standard normal cumulative distribution function.

The technical efficiency of the manufacturing sectors in Bangladesh will be estimated using the translog production function with one output and three inputs using the following:

$$\begin{aligned} \ln y_i = {} & \beta_0 + \beta_k \ln k_i + \beta_l \ln l_i + \beta_m \ln m_i + \beta_t t + \frac{1}{2}[\beta_{kk}(\ln k_i) + \beta_{ll}(\ln l_i) + \beta_{mm}(\ln m_i) + \beta_{tt}(\ln t_i)] \\ & + \beta_{kl} \ln k_i \ln l_i + \beta_{km} \ln k_i \ln m_i + \beta_{lm} \ln l_i \ln m_i + \beta_{kt} \ln k_i t + \beta_{lt} \ln l_i t + \beta_{mt} \ln m_i t \\ & + v_i - u_i \end{aligned}$$

Where $i = 1,2,3,\ldots,i$ denotes the individual industries. y is the output for each industry, and k, l and m are capital, labor and material, respectively. The maximum likelihood estimator (MLE) is used to obtain the point estimate of technical efficiency that is derived from the production function.

Total factor productivity growth is used to determine productivity, and TFP growth decomposition can be used to detect the sources of productivity (Kumbhakar & Lovell, 2000). $\dot{TFP}$ can be decomposed into three elements: (i) technological progress (TP), (ii) returns to scale component, (SE), and (iii) changes in technical efficiency ($\dot{TE}$). Technological change is the partial derivative of the production function with respect to time, the scale elasticity effect on TFP growth is defined as the scale component, and the technical efficiency derivative with respect to time is the technical efficiency change.

Technological progress is derived from the production function by:

$$\begin{aligned} TP &= \frac{\partial \ln y_{it}}{\partial t} \\ &= \beta_t + \beta_{tt} t + \beta_{kt} \ln k_{it} + \beta_{lt} \ln l_{it} + \beta_{mt} \ln m_{it} \end{aligned}$$

$$SC = (e-1)\sum_j \left(\frac{e_j}{e}\right)\dot{x}_j$$

Where $e_j, j = 1,2,3,\ldots,J$ are the output elasticities with respect to input $j, e = \sum_j e_j$ and $\dot{x}_j$ is the rate of change of inputx_j.

The change in technical efficiency change is estimated by:

$$\dot{TE} = -\frac{\partial u_{it}}{\partial t}$$
$$= \delta\, exp\,\{-\delta\,(t-T\}u_i$$

Total factor productivity growth decomposition from the production aspect is given as:

$$\dot{TFP} = TP + SE + \dot{TE}$$
$$= (\beta_t + \beta_{tt}t + \beta_{kt}\ \ln k_{it} + \beta_{lt}\ \ln l_{it} + \beta_{mt}\ \ln m_{it}) + (e-1)\sum_j \left(\frac{e_j}{e}\right)\dot{x}_j + \delta\eta_t u_i$$

4. Data

The data used for this study are collected from the Census of Manufacturing Industries (CMI) published by the Bangladesh Bureau of Statistics (BBS) and selected from five rounds of surveys: 1982/83, 1984/85, 1988/89, 2005/06, and 2012. Due to the inaccessibility of data for other years, surveys for 2005/2006 and 2012 are considered. The research is limited because of firm-level data inaccessibility; therefore, the subindustry totals will be applied as individual firms. The output data are gross value added, which is the value of gross total output minus intermediate consumption; capital, *k*, is fixed assets, which is obtained from other enterprises or produced by the establishment out of its resources for its own use and is expected to have a productive life of more than a year. This consists of land, machinery and equipment, buildings, transport, etc.; and labor, *l* is the mean of the total number of persons that work for or in the establishment, including working proprietors, unpaid family workers and partners; material, *m*, are the industrial costs incurred as the cost of raw materials, supplementary materials, supplies and packaging materials that have been directly incorporated in the products and by products, as well as payments for work done by others. All variables except labor are in millions of Taka. Stratification was performed following the size class based on the total persons employed (TPE). As a result, establishments were stratified into four size classes, namely, large (TPE 250 +), medium (TPE 100-250), and small (TPE 10-99) industries. This variable sheds some important light on the efficiency level of the industries in question. Additionally, we consider the orientation of the industries, dividing them into export and non-export industries.

5. Results

5.1 Efficiency Estimates: All Industries

Table 1 shows the parameter estimates of the translogarithmic production function. It can be seen that α_k and α_m are positive and statistically significant, showing that capital and material are important in the manufacturing sector in Bangladesh. Table 2 presents the average technical efficiency estimates of selected industries from the five rounds of survey 1982/83, 1984/85, 1988/89, 2005/06 and 2012 and the average overtime.

Table 1. Coefficient estimates of the translog production function.

Parameter	Variable	Estimate	Standard error
α_0	Intercept	2.435**	1.027
α_k	ln *k*	0.425**	0.206
α_l	ln *l*	0.102	0.230
α_m	ln *m*	0.412**	0.187
α_t	*T*	0.124	0.204
α_{kk}	0.5[ln *k*]^2	-0.025	0.017
α_{ll}	0.5[ln *l*]^2	0.017	0.025
α_{mm}	0.5[ln *m*]^2	0.071***	0.025
α_{kl}	[ln *k*][ln *l*]	0.067***	0.025
α_{km}	[ln *k*][ln *m*]	-0.020	0.018
α_{lm}	[ln *l*][ln *m*]	-0.0722***	0.019
α_{tt}	0.5t^2	0.020	0.028
α_{kt}	*t*[ln *k*]	0.008	0.017
α_{lt}	*t*[ln *l*]	-0.012	0.021
α_{lt}	*t*[ln *m*]	-0.008	0.015
σ_μ^2	-	0.082***	0.007
Γ	-	0.130**	0.064
Μ	-	0.206**	0.086
Η	-	0.029	0.085

Note: *** and ** denote significance at the 5 and 10% levels, respectively.

The table illustrates that, on average, technical efficiency was 80%; that is, technical inefficiency caused actual production to fall below its highest potential by 20%. This is higher than the technical efficiency estimates derived by Baten et al. (2009) and Baten et al. (2006), who examined manufacturing industries in Bangladesh. They found that, on average, mean technical efficiency was 34% and 40%, respectively, using the truncated normal distribution, and 36% and 56%, respectively, when the half-normal distribution was employed. However, it is comparable to the technical efficiency of 76% for manufacturing industries in Jordan Al-Durgham & Adeinat, (2020), and Kim and Han (2001) found that nonmetal and food industries have technical efficiency estimates of 0.833 and 0.775, respectively.

Table 2. industries average technical efficiency.

Industry	1982/1983	1984/1985	1988/1989	2005/2006	2012	Average	Rank
Dairy products	0.745	0.751	0.757	0.763	0.769	0.757	51
Fruits and vegetables	0.755	0.761	0.767	0.773	0.778	0.767	44
Fish and sea foods	0.754	0.760	0.766	0.771	0.777	0.766	45
Hydrogenated vegetable oils	0.743	0.749	0.755	0.761	0.767	0.755	52
Rice milling	0.701	0.708	0.715	0.722	0.729	0.715	58
Grain mill products	0.829	0.833	0.837	0.842	0.846	0.837	15
Bakery products	0.781	0.787	0.792	0.797	0.802	0.792	30
Sugar factories	0.773	0.778	0.784	0.789	0.794	0.784	35
Confectionaries	0.793	0.798	0.803	0.808	0.813	0.803	24
Manufacture and processing of tea and coffee	0.829	0.834	0.838	0.842	0.846	0.838	14
Soft drink manufacturing	0.785	0.790	0.795	0.800	0.805	0.795	28
Cigarettes	0.953	0.954	0.955	0.956	0.958	0.955	1
Zarda and quivam	0.805	0.809	0.814	0.819	0.823	0.814	20
Jute textiles	0.717	0.724	0.730	0.737	0.743	0.730	57
Handloom textiles	0.781	0.786	0.791	0.796	0.801	0.791	31
Dyeing bleaching textile	0.774	0.780	0.785	0.791	0.796	0.785	34
Carpets and rugs	0.736	0.743	0.749	0.755	0.761	0.749	54
Cordage rope and twine	0.724	0.731	0.737	0.744	0.750	0.737	55
Spooling and thread ball	0.738	0.745	0.751	0.757	0.763	0.751	53
Textile manufacturing	0.762	0.767	0.773	0.779	0.784	0.773	43
Ready-made garments	0.748	0.754	0.760	0.765	0.771	0.759	50
Tanning and finishing	0.749	0.755	0.761	0.767	0.773	0.761	49
Leather products	0.834	0.838	0.843	0.847	0.851	0.843	10
Jute pressing and balling	0.768	0.774	0.779	0.784	0.790	0.779	39
Saw and planning mills	0.771	0.777	0.783	0.788	0.793	0.782	37
Wooden furniture	0.791	0.796	0.801	0.806	0.811	0.801	25
Pulp and paper	0.721	0.728	0.735	0.741	0.747	0.734	56
Paper board manufacturing	0.779	0.784	0.790	0.795	0.800	0.790	32
Allopathic and medicines	0.831	0.835	0.839	0.843	0.847	0.839	13
Unani medicines	0.833	0.837	0.841	0.845	0.849	0.841	11
Ayuro-vedic medicines	0.904	0.906	0.909	0.911	0.913	0.908	3
Homeopathic and biochemic	0.807	0.812	0.817	0.821	0.826	0.817	19

Industry	1982/1983	1984/1985	1988/1989	2005/2006	2012	Average	Rank
Fertilizer's manufacturing	0.876	0.880	0.883	0.886	0.889	0.883	5
Manufacture of paints and ink	0.839	0.843	0.847	0.851	0.854	0.847	8
Manufacture of soaps and perfume	0.838	0.842	0.846	0.850	0.854	0.846	9
Matches manufacturing	0.646	0.654	0.662	0.670	0.677	0.662	59
Tar and Alkarta manufacture	0.765	0.771	0.777	0.782	0.787	0.776	40
Chemical products manufacture	0.763	0.769	0.775	0.780	0.786	0.775	41
Petroleum refining	0.789	0.794	0.799	0.804	0.809	0.799	26
Manufacture of rubber tyres and tubes	0.772	0.777	0.783	0.788	0.793	0.783	36
Rubber products	0.803	0.808	0.813	0.817	0.822	0.812	21
China and ceramic	0.823	0.827	0.832	0.836	0.840	0.831	16
Manufacture of glass and glass products	0.831	0.835	0.839	0.843	0.847	0.839	12
Bricks tiles and clay product	0.897	0.899	0.902	0.905	0.907	0.902	4
Cement products	0.822	0.827	0.831	0.835	0.840	0.831	17
Refractories manufacturing	0.874	0.877	0.880	0.883	0.886	0.880	6
Nonmetallic mineral	0.788	0.793	0.798	0.803	0.808	0.798	27
Manufacture of hand tools, cutlery and general hardware	0.751	0.757	0.763	0.769	0.774	0.763	46
Furnitures and fixtures metal	0.783	0.788	0.794	0.799	0.804	0.794	29
Structural metal products	0.775	0.780	0.786	0.791	0.796	0.786	33
Wire products	0.750	0.756	0.762	0.768	0.773	0.762	48
Fabricated metal products	0.763	0.769	0.774	0.780	0.785	0.774	42
Turbines and engines	0.770	0.776	0.781	0.787	0.792	0.781	38
Agricultural equipment	0.751	0.757	0.763	0.769	0.774	0.763	47
Batteries	0.840	0.844	0.848	0.852	0.855	0.848	7
Ship building and repairing	0.797	0.802	0.807	0.811	0.816	0.806	22
Motor vehicles	0.927	0.929	0.931	0.932	0.934	0.931	2
Optical goods	0.793	0.798	0.803	0.808	0.813	0.803	23
Other manufacturing industry	0.812	0.816	0.821	0.825	0.830	0.821	18
Average	0.791	0.796	0.801	0.806	0.811	0.801	

The cigarette industry is the most efficient, with a technical efficiency of approximately 96%, which may be attributed to Bangladesh being one of the largest tobacco-consuming countries in the world and the 12th largest tobacco producer in the world. Although the cigarette industry is taxed higher than most industries, it is still able to be efficient by offering a wide range of products ranging from mid-priced and low-priced cigarettes for smokers with low income to premium brands. Additionally, the major manufacturer of cigarettes in Bangladesh, which is the British American Tobacco Bangladesh (BAT Bangladesh), is a part of the British American Tobacco plc, one of the most prominent and established businesses in the world; therefore, BAT Bangladesh is able to draw from the managerial experiences of its international counterpart to run an effective business, thereby increasing its efficiency. The result also shows that the average technical efficiency of all industries improved over time.

Table 3. Beta convergence.

Variable	Coefficients
TE	-0.016***
	-0.005
TP	-0.507***
	-0.034
SC	-0.406***
	-0.053
TFP	-0.803***
	-0.062

Note: ***denote significance at the 10% levels, respectively.

5.2. Beta Convergence

The result in Table 3 shows that the coefficient of β_1 is negative and statistically significant for all variables. This indicates that the technical efficiencies, scale component, technological progress, and total factor productivity of the manufacturing industries in Bangladesh are converging for the periods under review.

The trend in technical efficiencies, scale component, technological progress, and total factor productivity among the manufacturing industries in Bangladesh shows the likelihood for convergence over time. This is examined by the convergence proposed by Baumol (1986). This is expressed as:

$$\ln\frac{TE_l}{TE_0} = \beta_0 + \beta_1 \ln TE_0 + \vartheta$$
$$\ln\frac{TC_l}{TC_0} = \beta_0 + \beta_1 \ln TC_0 + \vartheta$$
$$\ln\frac{SC_l}{SC_0} = \beta_0 + \beta_1 \ln SC_0 + \vartheta$$
$$\ln\frac{TFP_l}{TFP_0} = \beta_0 + \beta_1 \ln TFP_0 + \vartheta$$

Where TE_0 and TE_l are the averages (over industries) of the first and last period's technical efficiencies, TP_0 and TP_l are the averages (over industries) of the first and last period's technological progress, SC_0 and SC_l are the averages (over industries) of the first and last period's scale component, where TFP_0 and TFP_l are the averages (over industries) of the first and last period's total factor productivity, and ϑ is the random error term. If the coefficient of β_1 is negative and statistically significant, then we can conclude that there is β-convergence (Baumol, 1986).

Table 4. Elasticities of output with respect to capital, labor and material.

Industry	e_k	e_l	e_m	e
Dairy products	0.041	0.133	0.856	1.030
Fruits and vegetables	0.019	0.073	0.903	0.995
Fish and sea foods	0.040	0.034	0.936	1.010
Hydrogenated vegetable oils	0.036	-0.051	0.983	0.969
Rice milling	0.122	0.098	0.816	1.036
Grain mill products	0.030	-0.001	0.946	0.975
Bakery products	0.116	0.084	0.828	1.028
Sugar factories	0.126	0.130	0.791	1.047
Confectionaries	0.069	0.009	0.901	0.980
Manufacture and processing of tea and coffee	0.125	0.146	0.784	1.055
Soft drink manufacturing	0.043	0.136	0.853	1.032
Cigarettes	0.072	0.046	0.897	1.015
Zarda and quivam	0.080	0.007	0.884	0.971
Jute textiles	0.198	0.160	0.716	1.074
Handloom textiles	0.229	0.073	0.735	1.037
Dyeing bleaching textile	0.100	0.122	0.818	1.039
Carpets and rugs	0.046	0.254	0.767	1.067
Cordage rope and twine	0.068	0.079	0.863	1.010
Spooling and thread ball	0.062	0.136	0.831	1.030
Textile manufacturing	0.037	0.110	0.864	1.011

Industry	e_k	e_l	e_m	e
Ready-made garments	0.194	0.087	0.767	1.048
Tanning and finishing	0.058	0.030	0.923	1.010
Leather products	0.068	0.102	0.860	1.031
Jute pressing and balling	0.077	-0.008	0.918	0.988
Saw and planning mills	0.108	0.032	0.853	0.993
Wooden furniture	0.128	0.066	0.822	1.016
Pulp and paper	0.062	0.140	0.843	1.046
Paper board manufacturing	0.052	0.092	0.872	1.016
Allopathic and medicines	0.106	0.128	0.816	1.050
Unani medicines	0.101	0.103	0.805	1.009
Ayuro-vedic medicines	0.113	0.096	0.806	1.015
Homeopathic and biochemic	0.082	0.086	0.830	0.998
Fertilizers manufacturing	-0.010	0.213	0.866	1.069
Manufacture of paints and ink	0.038	0.076	0.895	1.008
Manufacture of soaps and perfume	0.078	0.043	0.892	1.013
Matches manufacturing	0.143	0.137	0.758	1.038
Tar and alkarta manufacture	-0.008	-0.059	1.014	0.947
Chemical products manufacture	0.023	0.078	0.892	0.993
Petroleum refining	-0.078	-0.022	1.070	0.970
Manufacture of rubber tyres and tubes	0.041	0.036	0.910	0.987
Rubber products	0.070	0.091	0.858	1.019
China and ceramic	0.075	0.180	0.788	1.043
Manufacture of glass and glass products	0.055	0.143	0.835	1.033
Bricks tiles and clay product	0.194	0.130	0.723	1.046
Cement products	0.006	0.069	0.941	1.016
Refractories manufacturing	0.052	0.076	0.866	0.994
Nonmetallic mineral	0.035	0.041	0.917	0.993
Manufacture of cutlery, hand tools and general hardware	0.085	0.063	0.854	1.001
Furnitures and fixtures metal	0.105	0.062	0.836	1.002
Structural metal products	0.089	0.090	0.838	1.018
Wire products	0.034	0.032	0.925	0.991
Fabricated metal products	0.099	0.050	0.858	1.007
Engines and turbines	0.019	0.176	0.837	1.033
Agric. machinery equipment	0.050	0.129	0.836	1.015
Batteries	0.064	0.040	0.897	1.002
Ship building and repairing	0.075	0.144	0.819	1.038
Motor vehicles	0.031	-0.066	1.000	0.965
Optical goods	0.062	0.006	0.904	0.972
Other manufacturing industry	0.026	0.080	0.893	1.000

5.3. Output Elasticities

We examine the extent to which output increases when there is an increase in input level. This is done by examining the elasticity of output with respect to labor, capital, and material.

The output elasticity with respect to capital is given as:

$$e_k = \frac{\partial \ln y}{\partial \ln k}$$
$$= \beta_k + \beta_{kk} \ln k_{it} + \beta_{kl} \ln l_{it} + \beta_{km} \ln m_{it} + \beta_{kt} t,$$

Output elasticity with respect to labor is calculated as:

$$e_l = \frac{\partial \ln y}{\partial \ln l}$$
$$= \beta_l + \beta_{ll} \ln l_{it} + \beta_{kl} \ln k_{it} + \beta_{lm} \ln m_{it} + \beta_{lt} t,$$

Output elasticity with respect to labor is calculated as:

$$e_m = \frac{\partial \ln y}{\partial \ln m}$$
$$= \beta_m + \beta_{mm} \ln m_{it} + \beta_{mk} \ln k_{it} + \beta_{ml} \ln l_{it} + \beta_{mt} t$$

In Table 4, we consider the output elasticities with respect to labor, e_l, capital, e_k and material, e_m. The table reports the elasticities of output at the mean values for each industry. The mean value of labor elasticity across the sample is 0.0809, capital is 0.0722, and material is 0.8611. The elasticity of output with respect to labor varies across industries, ranging from -0.0775 for the petroleum refining industry to 0.02288 for the handloom textiles industry. This means that for every 1% increase in labor, the output will increase by 0.02% for the handloom textiles industry and decrease by 0.08% for the petroleum refining industry. A possible explanation for the decline in output with respect to the petroleum refining industry is that Bangladesh has only one refinery that is largely dependent on oil imports, and oil exploration has been largely unsuccessful, resulting in additional capital inputs having no positive impact on output. Additionally, due to losses recorded by the Bangladesh Petroleum Corporation (BPC), the state-owned distributor of petroleum products, the government had to increase prices by approximately 10 and 20 percent.

For output elasticity with respect to labor, the values range from -0.0661 for the motor vehicles industry to 0.2536 for the carpets and rugs industry. This means that if labor increases by 1%, the output will increase by 0.25% in the carpets and rugs industry. Most of the carpets and rugs that are produced and exported in Bangladesh are hand woven and are highly labor intensive, requiring four people working for twelve hours in a day to finish a large 198 by 198 inches of carpet in two months (Kara, 2014).

For output elasticity with respect to material, the values range from 0.7156 for the jute textiles industry to 1.0698 for the petroleum refining industry. This means that if material increases by 1%, the output will increase by approximately 0.72% in the jute textiles industry.

Furthermore, when we compare the output elasticities with respect to labor, capital and material, we can conclude that the outputs of the industries in the review are driven more by material than capital and labor.

5.4. Total Factor Productivity

Table 5 presents the yearly averages of the TFP growth components and shows details of how TFP, scale component, technological progress, and technical efficiency vary over time. Technical efficiency, on average, has been declining for the period in review, starting at 0.66% in 1982-83 to 0.61% by 2012. The decline in efficiency corresponds to technological progress, as is expected. This is in line with the results shown by Hassan et al. (2010) and Coelli, Rahman, and Thirtle (2003).

The industry scale effect suggests that, on average, the scale component grew by 1.28%, indicating positive changes among the industries under review. The scale component varied on average between 0.74 and 2.07, which suggests that the industries exhibited increasing returns to scale in 1988-89 and 2005-06, and decreasing returns to scale in 1984-85 and 2012. Considering the entire period, there were increasing returns to scale, which is evident from the fact that the total elasticities of output, *e*, are greater than one. Technological progress on average continued to increase throughout the period in review.

Total factor productivity growth was, on average, 5.5% for the period under review. Although the result exhibits positive total factor growth in all the periods, there was a slight dip in 2012. The industries that experienced negative TFP growth in this period were the grain mill products industry, hydrogenated vegetable oil industry, wire products industry, optical goods industry, and motor vehicle industry. It is worth noting that even with the decline in total factor productivity growth in 2012, technological progress was the highest contributor to TFP growth in this period. TFP growth mainly comes from technological progress, and this is reassuring because changes in efficiency can no longer be positive once the frontier is reached. The table shows that for the period under review, technological progress surpassed efficiency changes and the scale component for the industries. Therefore, technological progress has contributed more significantly to TFP growth than changes in efficiency and scale component.

Table 5. Average total factor productivity growths and its components.

Year	TEC	TP	SC	TFP
1982/1983	-	-	-	-
1984/1985	0.659	1.457	0.743	2.858
1988/1989	0.641	3.051	1.376	5.067
2005/2006	0.623	4.377	2.069	7.068
2012	0.606	5.356	0.931	6.893
Average	0.632	3.560	1.280	5.471

5.5. Efficiency Estimates: Industry Size

Figures 1 to 4 present the efficiency estimates and TFP components of industries by size. In this section, we examine whether technical efficiency and TFP growth differ among industries due to their size. The industries are divided into 3 classes with respect to the total persons engaged following the classification in the surveys of the manufacturing industry performed by the Bangladesh Bureau of Statistics (BBS). The small industries are those with fewer than 99 total persons engaged, while the medium industries range from 100 to fewer than 250 total persons engaged, and the large industries have more than 250 total persons engaged. The technical efficiency estimates show that technical efficiency had an upward trend and then a decline after the third survey. This can also be seen in the technical efficiency changes for the period under review. For small industries, technical efficiency gradually increased until its decline in 1988-89, while that of large industries experienced a steady increase for the period under view. It is interesting to note that the industries (small, medium and large) seem to converge during the third round of the survey used in this study for technical efficiency estimates and technical efficiency changes. A possible explanation for this is that Bangladesh experienced one of the worst floods of the twentieth century in 1988. The flood, called the flood of the century, covered two-thirds of Bangladesh, leading to the destruction of infrastructures used for manufacturing and caused difficulty in mobility. As a result, individuals who were employed could not even get to their places of work.

The large industries experienced economies of scale for all the periods under review. On average, the scale economy factor for small industries with fewer than 99 total persons engaged was -0.4334, and -1.0966 for medium industries with 100 to fewer than 250 total persons engaged, while big industries with more than 250 total persons engaged had a scale economy factor of 1.4931. The result shows that only large industries experienced economies of scale, with small and medium industries experiencing diseconomies of scale. Technological progress with respect to different industry sizes shows the presence of TP for all industries, irrespective of its size. However, mid-sized industries have the highest level of technological progress, followed by small and large industries. Total factor productivity was highest among the small-sized firms, with TFP growth of 6.9%, while medium- and large-sized firms had TFP growth of 6.4% and 5.2%, respectively. This is in line with Fernandes (2008), who found that firms of smaller sizes have higher TFP relative to extremely large manufacturing firms. There was positive total factor growth in all the periods, with a slight dip in 2005/2006 for the small industries, which could be a result of the 2005 flood, where the small industries did not have the necessary equipment or infrastructures to mitigate the effect of the flood. Additionally, our results show that technological progress was the highest contributor to TFP growth irrespective of industry size.

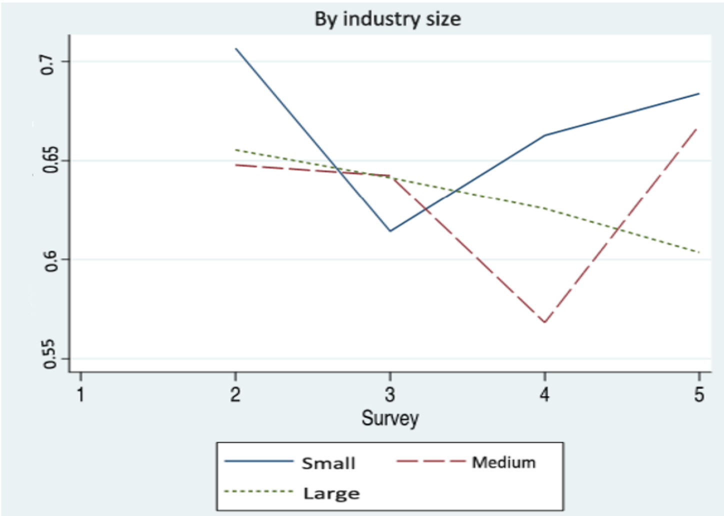

Figure 1. Average technical efficiency change.

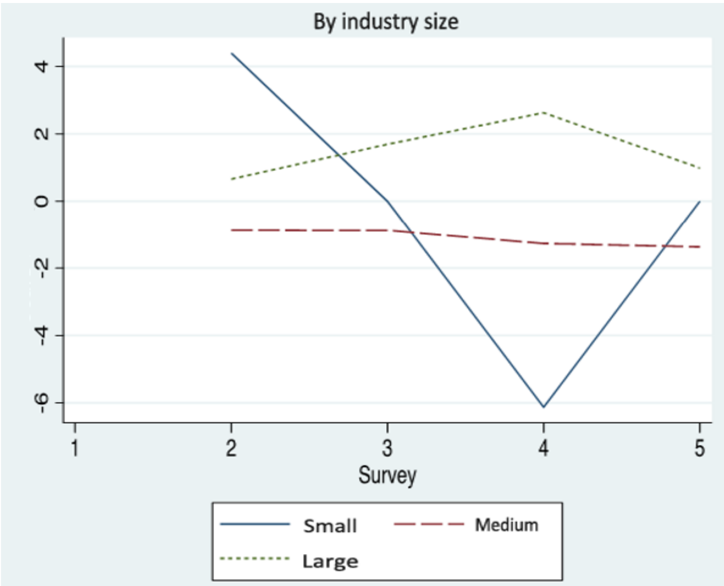

Figure 2. Scale component.

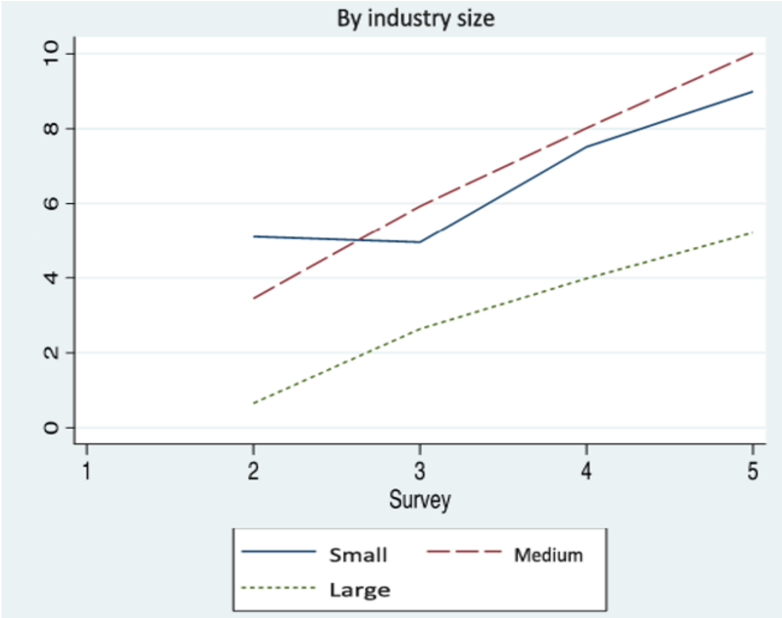

Figure 3. Technological progress.

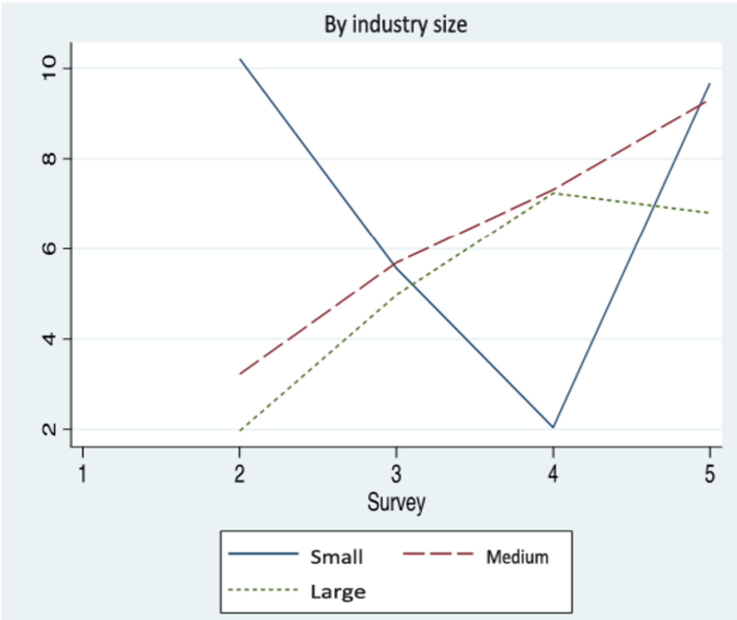

Figure 4. Total factor productivity.

5.5. Efficiency Estimates: Industry Orientation

Figures 5 to 8 present the efficiency estimates and TFP components by industry orientation. In this section, we examine whether technical efficiency and TFP growth differ among industries due to their orientation. The industries are divided into 2 classes: export and nonexport industries. Our results show that average technical efficiency was higher among export-oriented industries. This is in line with findings by Hossain and Karunaratne (2004), who suggested that trade liberalization, proxied by export orientation, has a significant impact on the reduction of the overall technical inefficiency among Bangladeshi manufacturing industries. Additionally, Hassan et al. (2010) showed that trade liberalization policies in the 1990s had positive effects on the efficiency of export-oriented industries. This is because export-oriented industries are more competitive and have access to advanced technologies, but nonexport-oriented industries are immensely protected through quotas or tariffs, which makes them less competitive and slows to adjust to trade liberalization. On the other hand, average technical efficiency changes have been declining over time.

Figures 5 to 8 show that export-oriented industries experienced economies of scale for most of the periods in review. The figures show that diseconomies of scale were experienced by the nonexport-oriented industries for most of the periods in review, with the only exception in 2005/2006. Technological progress with respect to industry orientation shows the presence of TP for all industries irrespective of its orientation, but nonexport industries have higher levels of technological progress than export-oriented industries. Total factor productivity was positive for both export and nonexport industries. TFP growth was higher in export industries as a result of economies of scale and technological progress, with technological progress being a major contributor. For nonexport industries, technological progress and efficiency changes contributed to TFP growth, and technological progress was a major contributing component.

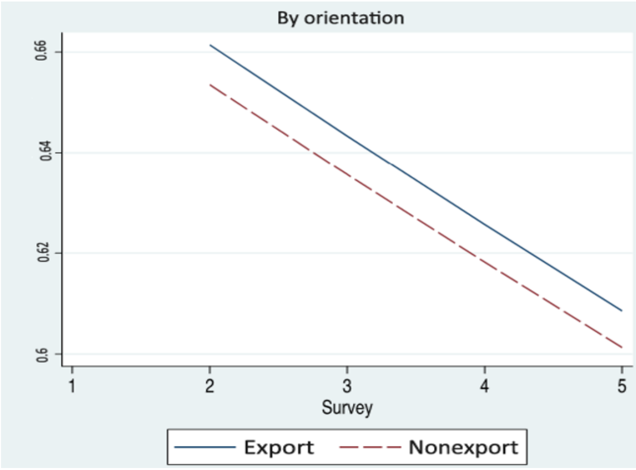

Figure 5. Average technical efficiency change.

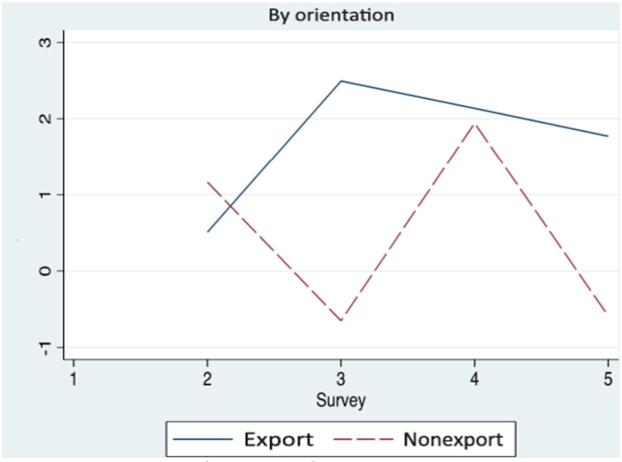

Figure 6. Scale component.

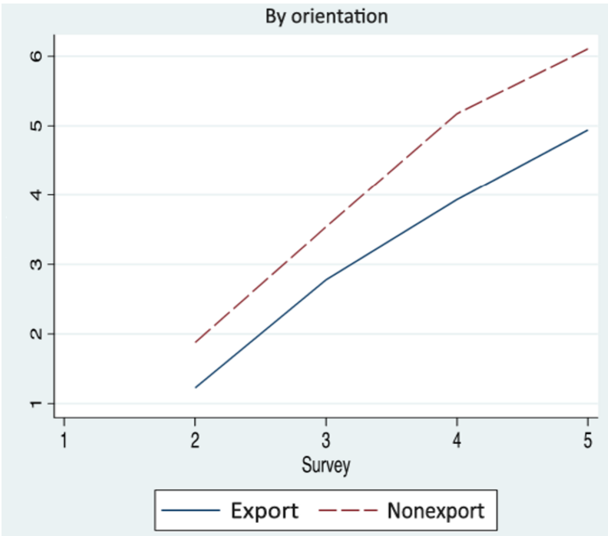

Figure 7. Technological progress.

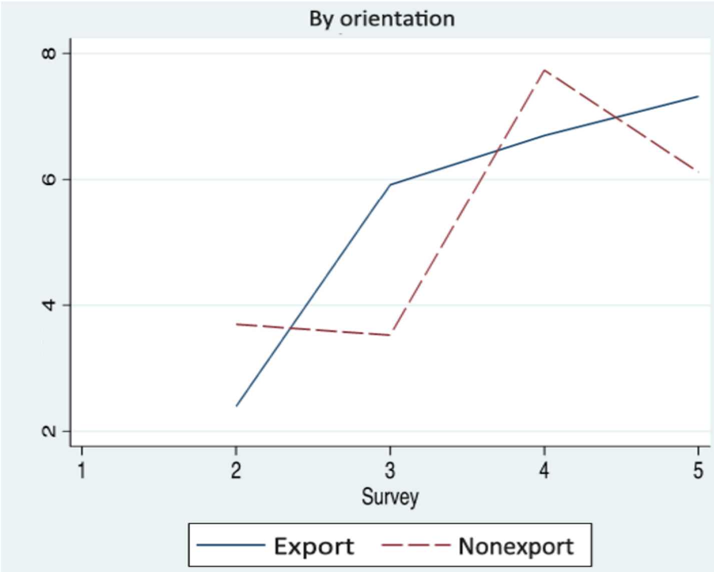

Figure 8. Total factor productivity.

6. Conclusion

In conclusion, this study aimed to estimate the technical efficiency, technological progress, scale economy and total factor productivity for manufacturing industries in Bangladesh. Using five rounds of survey data from 1982/83, 1984/85, 1988/89, 2005/06, and 2012, the translog production function was utilized along with a decomposition approach. This method allowed us to relax the assumption that inputs are efficiently utilized, making the results more applicable to real-world scenarios. The results showed that on average, technical efficiency was 80%, higher than previous studies conducted by Baten et al. (2009) and Baten et al. (2006), who estimated an average mean technical efficiency of 34% to 56% using the truncated normal distribution and half-normal distribution, respectively. Our findings reveal that technical efficiency was consistent across large and medium-sized industries, with only large industries enjoying economies of scale while small and medium industries faced diseconomies of scale. Additionally, our results indicate that export-oriented industries had higher technical efficiency compared to non-export-oriented industries. This study highlights the convergence of technical efficiencies, scale components, technological progress, and TFP for the manufacturing industries in Bangladesh over the period that was studied.

In summary, the 5.5% average total factor productivity growth during the studied period was largely driven by advancements in technology, outpacing changes in efficiency and scale components. Our findings call for further examination of TFP and efficiency in the manufacturing sector of Bangladesh, as the country, a developing nation, has substantial potential to enhance its industries' productivity and raise its income levels. Avenues for further studies include exploring the differences in TFP and technical efficiency across regions, industries, and firm size groups within Bangladesh, as well as applying deep learning and compare with different econometric techniques to validate the results with previous studies. Additionally, conducting case studies of specific industries could provide in-depth insights into the sources of TFP growth and technical efficiency.

References

Aigner, D., Lovell, C., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics, 6*(1), 21-37. https://doi.org/10.1016/0304-4076(77)90052-5

Al-Durgham, L., & Adeinat, M. (2020). Efficiency of listed manufacturing firms in Jordan: A stochastic frontier analysis. *International Journal of Economics and Financial Issues, 10*(6), 5-9. https://doi.org/10.32479/ijefi.10489

Auci, S., & Vignani, D. (2020). Climate variability and agriculture in Italy: A stochastic frontier analysis at the regional level. *Economia Politica, 37*(2), 381-409. https://doi.org/10.1007/s40888-020-00172-x

Autor, D., & Salomons, A. (2018). *Is automation labor-displacing? Productivity growth, employment, and the labor share.* Retrieved from National Bureau of Economic Research. Working Paper No. w24871.

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 and Applied Sciences, 3*(2), 1160-1169.

Baten, M. A., Rana, M., Das, S., & Khaleque, M. A. (2006). Technical efficiency of some selected manufacturing industries in Bangladesh: A stochastic frontier analysis. *Lahore Journal of Economics, 11*(2), 23-41. https://doi.org/10.35536/lje.2006.v11.i2.a2

Battese, G., & Coelli, T. (1992). Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis, 3*(1-2), 153-169. https://doi.org/10.1007/bf00158774

Battese, G. E., & Coelli, T. J. (1988). Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics, 38*(3), 387-399. https://doi.org/10.1016/0304-4076(88)90053-X

Baumol, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *The American Economic Review, 76*(5), 1072–1085.

Benedetti, I., Branca, G., & Zucaro, R. (2019). Evaluating input use efficiency in agriculture through a stochastic frontier production: An application on a case study in Apulia Italy. *Journal of Cleaner Production, 236*, 117609. https://doi.org/10.1016/j.jclepro.2019.117609

Bhaumik, S. K., Das, P. K., & Kumbhakar, S. C. (2012). A stochastic frontier approach to modelling financial constraints in firms: An application to India. *Journal of Banking & Finance, 36*(5), 1311-1319. https://doi.org/10.1016/j.jbankfin.2011.11.026

Bibi, Z., & Khan, D. (2021). Technical and environmental efficiency of agriculture sector in South Asia: A stochastic frontier analysis approach. *Environment, Development and Sustainability: A Multidisciplinary Approach to the Theory and Practice of Sustainable Development, 23*(6), 9260-9279. https://doi.org/10.1007/s10668-020-01023-2

Cabrera-Suárez, I., & Pérez-Rodríguez, J. V. (2021). Bank branch performance and cost efficiency: A stochastic frontier panel data approach. *International Journal of Finance & Economics, 26*(4), 5850-5863. https://doi.org/10.1002/ijfe.2097

Cainelli, G., Ganau, R., & Giunta, A. (2018). Spatial agglomeration, global value Chains, and productivity. Micro-evidence from Italy and Spain. *Economics Letters, 169*(C), 43-46. https://doi.org/10.1016/j.econlet.2018.04.020

Chen, X., Liu, X., & Zhu, Q. (2022). Comparative analysis of total factor productivity in China's high-tech industries. *Technological Forecasting and Social Change, 175*(C), 121332. https://doi.org/10.1016/j.techfore.2021.121332

Coelli, T., Rahman, S., & Thirtle, C. (2003). A stochastic frontier approach to total factor productivity measurement in Bangladesh crop agriculture, 1961–92. *Journal of International Development: The Journal of the Development Studies Association, 15*(3), 321-333. https://doi.org/10.1002/jid.975

Fernandes, A. M. (2008). Firm productivity in Bangladesh manufacturing industries. *World Development, 36*(10), 1725-1744. https://doi.org/10.1016/j.worlddev.2008.01.001

Gupta, H., Kumar, A., & Wasan, P. (2021). Industry 4.0, cleaner production and circular economy: An integrative framework for evaluating ethical and sustainable business performance of manufacturing organizations. *Journal of Cleaner Production, 295*, 126253. https://doi.org/10.1016/j.jclepro.2021.126253

Gupta, S. D., Raychaudhuri, A., & Haldar, S. K. (2018). Information technology and profitability: Evidence from Indian banking sector. *International Journal of Emerging Markets, 13*(5), 1070-1087. https://doi.org/10.1108/ijoem-06-2017-0211

Hassan, M. K., Isik, I., & Mamun, A. (2010). Trade liberalization and industry performance in Bangladesh. *Journal of Policy Modeling, 32*(3), 399-417. https://doi.org/10.1016/j.jpolmod.2010.02.005

Hossain, M., & Karunaratne, N. D. (2004). Trade liberalisation and technical efficiency: Evidence from Bangladesh manufacturing industries. *Journal of Development Studies, 40*(3), 87-114. https://doi.org/10.1080/0022038042000213210

Husain, S., & Islam, M. (2016). A test for the cobb douglas production function in manufacturing sector: The case of Bangladesh. *International Journal of Business and Economics Research, 5*(5), 149-154. https://doi.org/10.11648/j.ijber.20160505.13

Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management, 103*, 102360. https://doi.org/10.1016/j.jeem.2020.102360

Kara, S. (2014). *Tainted carpets: Slavery and child labor in India's hand-made carpet sector*. Retrieved from FXB Center for Health and Human Rights. Arpet Sector', Report for FXB Center for Health and Human Rights, Harvard School of Public Health, Harvard University, Boston, MA.

Kaynak, H., & PagÁn, J. A. (2003). Just-in-time purchasing and technical efficiency in the US manufacturing sector. *International Journal of Production Research, 41*(1), 1-14. https://doi.org/10.1080/00207540210161696

Kim, S., & Han, G. (2001). A decomposition of total Factor productivity growth in Korean manufacturing industries: A stochastic frontier approach. *Journal of Productivity Analysis, 3*(16), 269-281.

Kirjavainen, T. (2012). Efficiency of Finnish general upper secondary schools: An application of stochastic frontier analysis with panel data. *Education Economics, 20*(4), 343-364. https://doi.org/10.1080/09645292.2010.510862

Koh, S. W., Rahman, S., & Tan, G. R. (2002). Growth and productivity in Singapore manufacturing industries: 1975–1998. *Asian Economic Journal, 16*(3), 247-266. https://doi.org/10.1111/1467-8381.t01-1-00151

Kumbhakar, S., & Lovell, K. (2000). *Stochastic frontier analysis*. Cambridge: Cambridge University Press.

Kumbhakar, S. C. (1990). Production frontiers, panel data, and time-varying technical inefficiency. *Journal of Econometrics, 46*(1-2), 201-211. https://doi.org/10.1016/0304-4076(90)90055-X

Kumbhakar, S. C., & Tsionas, M. G. (2021). Dissections of input and output efficiency: A generalized stochastic frontier model. *International Journal of Production Economics, 232*(C), 107940. https://doi.org/10.1016/j.ijpe.2020.107940

Lai, H.-P., & Kumbhakar, S. C. (2018). Panel data stochastic frontier model with determinants of persistent and transient inefficiency. *European Journal of Operational Research, 271*(2), 746-755. https://doi.org/10.1016/j.ejor.2018.04.043

Liu, R. (2019). Comparison of bank efficiencies between the US and Canada: Evidence based on SFA and DEA. *Comparison of Bank Efficiencies between the US and Canada: Evidence Based on SFA and DEA. Journal of Competitiveness, 11*(2), 113-129. https://doi.org/10.7441/joc.2019.02.08

Margono, H., & Sharma, S. C. (2006). Efficiency and productivity analyses of Indonesian manufacturing industries. *Journal of Asian Economics, 17*(6), 979-995. https://doi.org/10.1016/j.asieco.2006.09.004

Meeusen, W., & Den, B. J. (1977). Efficiency estimation from cobb–douglas production functions with composed error. *International Economic Review, 18*(3), 435-444. https://doi.org/10.2307/2525757

Mehmood, Y., Rong, K., Bashir, M., & Arshad, M. (2018). Does partial quantity rationing of credit affect the technical efficiency of dairy farmers in Punjab, Pakistan? An application of stochastic frontier analysis. *British Food Journal.* https://doi.org/10.1108/BFJ-03-2017-0162

Miao, Z., Baležentis, T., Shao, S., & Chang, D. (2019). Energy use, industrial soot and vehicle exhaust pollution—China's regional air pollution recognition, performance decomposition and governance. *Energy Economics, 83*, 501-514. https://doi.org/10.1016/j.eneco.2019.07.002

Mokhtarul Wadud, I. K. M. (2004). Technical efficiency in Australian textile and clothing firms: Evidence from the business longitudinal survey. *Australian Economic Papers*, *43*(3), 357-378. https://doi.org/10.1111/j.1467-8454.2004.00235.x

Oguchi, N., Amdzah, N. A. M., Bakar, Z., Abidin, R. Z., & Shafii, M. (2002). Productivity of foreign and domestic firms in the Malaysian manufacturing industry. *Asian Economic Journal*, *16*(3), 215-228. https://doi.org/10.1111/j.1467-8381.2002.00149.x

Olley, S., & Pakes, A. (1992). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, *64*(6), 1263-1297. https://doi.org/10.2307/2171831

Sadalia, I., Kautsar, M., Irawati, N., & Muda, I. (2018). Analysis of the efficiency performance of Sharia and conventional banks using stochastic frontier analysis. *Banks & Bank Systems*, *13*(2), 27-38. http://dx.doi.org/10.21511/bbs.13(2).2018.03

Samad, Q., & Patwary, F. (2002). Technical efficiency and technical change in the major manufacturing industries of Bangladesh. *The Bangladesh Development Studies*, *28*(1/2), 113-135.

Sheng, Y., Tian, X., Qiao, W., & Peng, C. (2020). Measuring agricultural total factor productivity in China: Pattern and drivers over the period of 1978-2016. *Australian Journal of Agricultural and Resource Economics*, *64*(1), 82-103. https://doi.org/10.1111/1467-8489.12327

Sony, M., & Naik, S. (2020). Key ingredients for evaluating industry 4.0 readiness for organizations: A literature review. *Benchmarking: An International Journal*, *27*(7), 2213-2232. https://doi.org/10.1108/bij-09-2018-0284

Szalavetz, A. (2019). Industry 4.0 and capability development in manufacturing subsidiaries. *Technological Forecasting and Social Change*, *145*(C), 384-395. https://doi.org/10.1016/j.techfore.2018.06.027

Tsukamoto, T. (2019). A spatial autoregressive stochastic frontier model for panel data incorporating a model of technical inefficiency. *Japan and the World Economy*, *50*(C), 66-77. https://doi.org/10.1016/j.japwor.2018.11.003

Wang, R., Wang, Q., & Yao, S. (2021). Evaluation and difference analysis of regional energy efficiency in China under the carbon neutrality targets: Insights from DEA and theil models. *Journal of Environmental Management*, *293*, 112958. https://doi.org/10.1016/j.jenvman.2021.112958

World Bank. (2019). *Global financial development report 2019/2020: Bank regulation and supervision a decade after the global financial crisis*. Retrieved from The World Bank: https://doi.org/10.1596/978-1-4648-1447-1