International Journal of Applied Economics, Finance and Accounting
ISSN 2577-767X
Vol. 22, No. 1, pp. 120-138
2025
DOI: 10.33094/ijaefa.v22i1.2287

Manufacturing Performance and Organizational Practices: Evidence from an Emerging Economy

Mohammad Alamgir Hossain[1*]
Walter Wehrmeyer[2]
Mona Chitnis[3]

[1,2]*Centre for Environment and Sustainability, University of Surrey, Guildford, UK.*
Email: biddduthedu@gmail.com
Email: w.wehrmeyer@surrey.ac.uk
[3]*School of Economics, University of Surrey, Guildford, UK.*
Email: m.chitnis@surrey.ac.uk

Keywords:
Frontier analysis
Manufacturing performance
Organizational practices
Partial frontier model
Technical efficiency.

JEL Classification:
C10; C14; D24; L25.

Received: *7 April 2025*
Revised: *12 April 2025*
Accepted: *3 June 2025*
Published: *13 June 2025*
(Corresponding Author)*

Abstract

Assessing productive efficiency is vital for enhancing the manufacturing sector's contribution to the economic growth of emerging countries like Bangladesh. However, there has been no research evaluating the productive efficiency of the manufacturing sector in Bangladesh concerning organizational factors. This study examines Bangladesh's manufacturing sector, concentrating on technical performance. It uncovers reasons for the sector's limited contribution to the nation's industrial foundation. Nonparametric frontier models were employed to estimate technical efficiency, revealing compelling insights via diverse econometric techniques. According to the results, the manufacturing performance in 2019 exhibited a heightened disparity across subsectors compared to 2012, with some subsectors improving their efficiency while others experiencing a decline. Organizational practices were identified as having a modest impact on manufacturing performance. Subsectors characterized by higher levels of labor intensity demonstrated significantly superior economic performance compared to other subsectors. Some previously efficient subsectors, such as luggage, printing, and cement production, lost efficiency, while cocoa, textiles, jute-related industries, chocolate, sugar confectionery, and polythene manufacturing showed improvement in recent years. In brief, Bangladesh's manufacturing sector's performance declined from 2012 to 2019, with widening industry disparities. Subsectors that generated export revenue displayed unsatisfactory performance, highlighting the need for organizational improvement.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not Applicable.
Transparency: The authors declare that the manuscript is honest, truthful and transparent, that no important aspects of the study have been omitted and that all deviations from the planned study have been made clear. This study followed all rules of writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

1. Introduction

The manufacturing industry is vital to a low-income economy's early development, as the history of economic development has shown (Rodriki, 2007). The growth of Bangladesh's manufacturing industry would also be crucial for the country's future development.

Although Bangladesh's manufacturing sector has made tremendous strides in producing finished items over the past 20 years, there is still doubt that it has the potential to spur structural changes that will boost the country's economic growth. The manufacturing sector's contribution to GDP in 2021 was 21.24%, significantly less than the service sector's 51.92% contribution. On the other hand, the manufacturing industry's current job growth trajectory is insufficient for long-term industrial growth. Only 14.82% of all jobs in 2019 were in manufacturing, a figure substantially lower than the proportion of manufacturing value added to GDP (20.1%), which shows that there are still obstacles to job growth that reflect a complex dynamic between job growth and economic growth on a broader scale in this sector. [1]

The primary factor contributing to the relatively low employment in this sector was the low level of manufacturing activities (Gu, Nayyar, & Sharma, 2021). Comprehending the composition of the manufacturing sector is key to unraveling its challenges in propelling economic growth, especially in employment and MVA (Manufacturing Value Added) to GDP enhancement. Notably, the focus should be on producer efficiency, as highlighted by the SDG 9 index analysis[2]. By analyzing real-world data, policymakers can address current issues and promote advancements in the manufacturing sector. This can be achieved by evaluating the technical efficiency of individual companies and industry segments and guiding targeted policies to enhance overall progress.

To date, there has been no research evaluating the productive efficiency of the manufacturing sector in Bangladesh concerning organizational factors. Assessing the technical efficiency of evolving manufacturing subsectors in Bangladesh introduces an opportunity to gauge the success of the perspective plan, 2010-2021 (General Economics Division, 2012). This decade-long strategy aimed to bolster productive efficiency in Bangladesh's manufacturing sector, fortify its industrial base, and expand export diversity. This study's analytical framework examines how industries utilized resources (labor, human-made capital, and natural capital) to yield tangible outputs between 2012 and 2019. As a result, the current study's findings provide metrics that can evaluate the accomplishments of the perspective plan.

Numerous studies, such as Belotti, Di Porto, and Santoni (2016); Odiri and Ideh (2021) and Roudaut and Vanhems (2012) have looked at the sources of performance and productivity differences in organizations and linked those gaps to internal and external factors. The topic's theoretical basis lies in various versions of the theories of the Firm. X-inefficiency theory of Leibenstein (1966) for instance, emphasizes the factors that motivate managers and employees; Institutional Economics highlights the significance of managers' responses to external factors (Furubotn & Richter, 2005) and the Capabilities Theory of Firms accentuates managers' capacity to adapt to external changes (Teece, 2019). Business Models are becoming more integrated with sustainability-related challenges as the idea of sustainable development gains traction (Camilleri, 2017). Despite the widespread acceptance of improved organizational practices' significance on productivity (Bloom & Van Reenen, 2007; Martin, Muûls, De Preux, & Wagner, 2012; Syverson, 2011) it is still unclear how and what specific strategic practices affect operational, financial, or environmental performance as well as factor productivity (Maes, Sels, & Roodhooft, 2005; Paul & Anantharaman, 2003; Siebers et al., 2008).

Many papers highlight the linkages between firm performance and several organizational practices (Bloom & Van Reenen, 2007; Bryson & Forth, 2018; Kumar & Dua, 2022; Paul & Anantharaman, 2003). However, the current study focused on four management tactics that have not been explored before, along with organizational characteristics, in the context of Bangladesh. Organizational policies that support employee well-being, such as incentives, social insurance, and other benefits, are likely to enhance productivity since they reward hard work (Bloom & Van Reenen, 2007; Gomez-Mejia & Welbourne, 1988; Heinrich & Marschke, 2010; Jones, Kalmi, & Kauhanen, 2010; Paul & Anantharaman, 2003) though disagreements and opposing viewpoints exist (Bregn, 2013; Odiri & Ideh, 2021; Park, 2022).

Since taxes affect the cost function and decision-making process, they also significantly impact a firm's performance. Tax payments may indicate a corporation's seriousness about following rules, implying a link between tax payments and manufacturing performance. Many studies show that taxation and corporate performance have an inverse relationship (Belotti et al., 2016; Gatsi, Gadzo, & Kportorgbi, 2013; Lazăr & Istrate, 2018; Pitulice, Stefanescu, Minzu, Popa, & Niculescu, 2016; Schwellnus & Arnold, 2008). However, this specific relationship has not been explored within Bangladesh's context. This gap in the literature motivated the authors of this study to include tax payment as one of the organizational practices to be investigated, aiming to establish its connection with productivity.

Moreover, this paper extended the analysis to investigate potential connections between productivity or firm performance and labor intensity—a prominent attribute observed in the majority of industrial units in countries with abundant labor supply, yet rarely examined in empirical research (Lazăr, 2016).

Uncertainty surrounds the manufacturing sector's readiness to sustain Bangladesh's rapid economic expansion. Increased productivity and efficiency at the company and subsector levels are required to strengthen the manufacturing sector and spur economic growth. Yet, a thorough investigation has not been conducted into the production efficiency of manufacturing companies and subsectors in Bangladesh. Analyzing manufacturing performance in creating value using advanced techniques would help design an optimal regulatory framework in line with sustainable development concepts. The knowledge of how to model manufacturing productivity with multiple outputs is still developing. Only a few studies have looked at the heterogeneity in technical efficiency across businesses and the effects of organizational traits on industrial sectors in the setting of emerging economies.

---

[1]Source: https://databank.worldbank.org.
[2] https://iap.unido.org/data/sdg-9-industry?p=BGD.

The relationship between Bangladesh's production patterns and economic success is unexplored. If the efficiency levels are inadequate, appropriate actions should be taken to upgrade them. Understanding the difference between an industry's current efficiency and the frontier of best practices may help to reduce the gap and improve in areas with underutilized production capacity. This study compares the production efficiency of industry segments to industry best practices, considering both economic and social outputs, using a nonparametric benchmarking approach.

Moreover, no study has examined the factors affecting performance variation in Bangladeshi manufacturing. Therefore, this paper links manufacturing firms' performance scores to incentive schemes for employees, social insurance policies, tax payments, and labor intensity, aiming to generate a new understanding. Specifically, this paper seeks to answer two research questions:

1. What are the prevailing technical performance trends in Bangladesh's manufacturing sector?
2. How do organizational practices impact production performance in Bangladesh's manufacturing industry?

The paper is organized into the following sections: Section 1 provides a brief introduction. Section 2 covers a literature review on manufacturing performance evaluation, the impact of organizational practices, and methodological considerations. Section 3 presents the data and methodology used in the study. Section 4 portrays the empirical results on subsector-level manufacturing performance in Bangladesh. Lastly, the final section concludes the study and offers policy implications.

2. Literature Review

The significance of productivity and efficiency in the manufacturing sector has been the subject of a few studies in Bangladesh over the years. Some of these studies have investigated the connection between manufacturing performance and economic growth in Bangladesh without necessarily quantifying the efficiency levels of specific firms or industries.

In Nath's (2021) analysis, a thorough examination was conducted to assess the structural changes within the manufacturing sector and identify the sources of manufacturing growth. The author shed light on the significance of various factors, such as the size of enterprises, market orientation, factor intensities, and sub-sectoral contributions to manufacturing growth, and detected sectors that enjoy comparative advantages or possess growth potentials for the future development of manufacturing in Bangladesh. The paper acknowledged the role of labor intensity, considering the country's factor endowment.

Gu et al. (2021) highlighted the importance of production efficiency enhancement in the manufacturing sector to strengthen its capacity to leverage long-term sustainable growth in Bangladesh. Some other papers have presented efficiency estimates for manufacturing units using the production function approach and changes in total factor productivity (TFP) over time. The reported efficiency scores from various studies exhibit varying magnitudes. One of the earliest contributions in this domain was by Krishna and Sahota (1991) who estimated technical efficiency and TFP growth in thirty crucial four-digit industries in Bangladesh. Their analysis relied on individual firm data from the Census of Manufacturing Industries (CMI) for 1974/75, 1975/76, and 1979/80 to 1985/86. The empirical results revealed that, during the study period, fifteen out of the thirty industries displayed no significant productivity changes. Only five industries experienced a notable acceleration in TFP change. Additionally, most industries exhibited substantial disparities in technical efficiency among firms.

However, this declining trend in most subsectors observed by Krishna and Sahota (1991) contradicted the findings of Hossain and Karunaratne (2004) who provided estimates of productivity changes in Bangladesh manufacturing subsectors using an extended dataset from the same data source employed by Krishna and Sahota (1991). In their study, which utilized subsector-level data, a different trend emerged. It indicated a notable increase in the average technical efficiency of the manufacturing sector from 1978 to 1994. Specifically, 22 of 25 industries demonstrated higher technical efficiency over time, with some showing statistically significant improvements and others displaying marginal gains. These findings contrast with the results reported by Krishna and Sahota (1991).

Samad and Patwary (2002) also utilized subsector-level data to compute efficiency scores. Their study indicated that the manufacturing sector's mean technical efficiency amounted to 0.85%. The research findings suggested a noticeable trend of increasing output elasticities for both capital and raw materials, which implies a transformation within the manufacturing sector during the observed period.

Contrary to Samad and Patwary (2002) and Baten, Rana, Das, and Khaleque (2006), reported much lower efficiency estimates. This paper, utilizing subsector-level panel data for 1981/82 to 1999/2000, conveyed that the manufacturing sector's overall efficiency ranged from 40.22% to 55.57% over the study period. Applying the same approach and using similar data, Baten, Rana, Das, and Nesa (2007) reported an estimated mean technical efficiency of 56.8%. In addition to technical efficiency estimates, this paper linked ownership type and geographical location to efficiency scores and discovered that private ownership positively influenced manufacturing performance, while the role of geographical location was found to be neutral.

A similar work was conducted by Baten, Kamil, and Fatama (2009). This paper reported that manufacturing efficiency ranged between 33.9% and 35.6% from 1988-89 to 1999-2000. The authors also presented rankings of subsectors based on their technical performance, with tobacco manufacturing at the top.

In a recent paper, investigated the technical efficiency and total factor productivity growth within Bangladesh's manufacturing sector. Over the review period (1982/83 to 2012), the study estimated a substantial total factor productivity growth rate of approximately 5.5% in Bangladesh's manufacturing sector. Moreover, the study revealed that the average technical efficiency of the manufacturing industries in Bangladesh stood at 80%, with export-oriented industries demonstrating higher efficiency than non-export industries. Additionally, small-scale industries exhibited superior total factor productivity growth compared to medium and large-scale industries. Furthermore, this work ranked subsectors based on efficiency scores. Tobacco manufacturing claimed the top position in this study, similar to the results of Baten et al. (2009).

Although these studies contributed much to understanding Bangladesh's manufacturing, their results suffered from several shortcomings. Earlier studies considered a limited number of inputs and outputs in the production function. This deficiency hampers a comprehensive understanding of the manufacturing dynamics in Bangladesh. The present work included various models integrating multiple outputs and inputs developed to describe the production process and provide valuable insights for promoting industrial development in the country.

Furthermore, most previous studies in Bangladesh adopted a stochastic frontier approach. This method is sensitive to distributional assumptions, so the findings are often criticized (Chen & Delmas, 2012; Sarkis, 2016; Tsang, Chen, Lu, & Chiu, 2014). Therefore, this current research employed nonparametric efficiency frontier methods to investigate manufacturing performance in Bangladesh.

The literature on measuring efficiency and productivity in manufacturing industries involving countries other than Bangladesh is vast and exhibits a growing preference for nonparametric frontier methods. Examples of research on estimating technical efficiency include (Alvarez & Crespi, 2003; Banker & Natarajan, 2008; Bhandari & Ray, 2012; Dalei & Joshi, 2020; Hoff, 2007; İlleez & Güner, 2018; McDonald, 2009; Ramalho, Ramalho, & Henriques, 2010).

Organizational practices play a crucial role in firm performance. The literature on firm performance and organizational practices has grown over the years, indicating a mounting interest in linking these two areas. Regrettably, the literature addressing this subject within the context of manufacturing in Bangladesh is limited. Only a few studies have established connections between firm performance and management or organizational practices specific to Bangladesh.

Rashid, Zobair, Shadek, Hoque, and Ahmad (2019) tried to judge the green performance of the Bangladesh manufacturing sector based on employees' perspectives on various social, economic, environmental, and organizational indicators. The results highlighted the importance of operational and corporate governance performance on green manufacturing performance in Bangladesh. However, this study's results relied exclusively on individual viewpoints and might have been affected by interviewees' perception levels, which might have introduced some bias.

In contrast, Roy et al. (2020) aimed to assess the cause-and-effect relationships between management strategies and supply chain performance measurement in Bangladesh's fast-moving consumer goods (FMCG) manufacturer. This research prioritized managerial strategies based on their effectiveness as environmental sustainability practices, proposing a method to gauge their impact on performance. Nevertheless, a significant limitation of their recommendations lies in the overly generalized concept of the strategies considered. For instance, the top-ranked strategy, 'material savings and better utilization of by-products,' encompassed various organizational approaches, such as paperless office work, water-saving schemes, rainwater facilities, and energy-saving initiatives. However, the lack of specificity in defining these strategies might hinder their precise implementation and measurement of their impact on supply chain performance.

While there is a significant dearth of published research concerning the analysis of firm performance and its correlation with organizational practices in Bangladesh, a substantial body of literature covers other economies. However, this literature has notable heterogeneity in measuring firm performance and identifying influential organizational practices (Lazăr, 2016). Many papers in this field tend to assess firm performance by relying on single or composite financial variables, such as sales, profit, and return on assets (ROA), among others.

For instance, Lazear (2000) examined the effect of incentives on labor productivity and company profitability using observation-based data. This paper found that switching from hourly wages to piece rates led to a 44% increase in the company's overall productivity, which could be decomposed into different effects. The incentive effect of the productivity acquisition caused a 22% productivity increase. In contrast, Paul and Anantharaman (2003) measured firm performance using several operational and financial indicators. It also utilized interviewees' opinions and supported the favorable impact of incentives on corporate performance.

Rather than concentrating solely on one country, Bloom and Van Reenen (2007) gathered data from manufacturing firms across four developed economies and conducted a cross-country analysis to reveal the connection between firm performance and management practices. Their work also affirmed a positive relationship between performance and effective management practices. Conversely, Odiri and Ideh (2021) suggested a negative association between performance and incentive schemes. They collected survey data in Nigeria, finding that motivational incentives and participative leadership harmed organizational performance.

Numerous studies have directed their attention toward the influence of corporate taxes on firm performance, consistently revealing a negative correlation. These investigations have employed firm-level data from both individual countries and multiple nations. For instance, Schwellnus and Arnold (2008) conducted a comprehensive analysis using a vast and representative dataset encompassing firms from OECD member countries, encompassing 287,727 observations. They employed the differences-in-differences methodology and found compelling evidence that corporate taxes negatively impacted firm-level productivity and investment.

Belotti et al. (2016) further elucidated the connection between taxation and firm performance by analyzing panel data from Italian manufacturing firms. Their findings corroborated an adverse relationship between tax payments and firm performance, as measured by total factor productivity. In a separate study, Lazăr and Istrate (2018) investigated Romanian businesses, utilizing return on assets (ROA) as a metric for firm performance. Their research revealed that a one-percentage-point increase in the overall firm-specific tax rate corresponded to a 0.15-percentage-point reduction in ROA.

Utilizing labor-intensive production techniques is a prevalent practice in many low-income countries. Nevertheless, there is a scarcity of research that explores the connection between firm performance and labor intensity. As an exception, Lazăr (2016) included labor intensity as one of the organizational practices in their study, examining its relationship with performance using data from Romanian business firms. The findings revealed a negative association between firm performance, measured by ROA, and labor intensity.

The performance measurement techniques employed in the studies mentioned above were limited in scope as they failed to encompass the fundamental spectrum that accounts for the flow of inputs and outputs. In contrast, with the evolution of production frontier-based methodologies, many publications have endeavored to evaluate firm performance using these approaches while establishing connections to organizational characteristics and practices. An example of this sort of research is the study conducted by Halkos and Tzeremes (2010) in which they evaluated the performance of Greek manufacturing firms using Data Envelopment Analysis and correlated it with ownership types. Their findings revealed that foreign ownership had a beneficial impact on the performance of foreign equities.

Conversely, Joshi and Singh (2012) established connections between outstanding loans, labor productivity, wages per employee, and the labor-staff ratio with nonparametric efficiency scores. They conducted this analysis using micro-level data from the Indian garments industry. In a separate study, Roudaut and Vanhems (2012) employed micro-level data from Cote d'Ivoire to investigate the relationship between technical efficiency and organizational characteristics such as age, ownership, export-orientation, and the presence of unions. The authors' findings indicated that ownership and export orientation were associated with performance levels only in low-technology firms and not in high-technology ones.

In contrast to studies based on micro-level data, Wang, Han, and Yin (2016) employed subsector-level data in China to examine the relationship between firm performance and organizational practices. The empirical findings demonstrated that factors such as the degree of openness, industry scale, and energy consumption were crucial indicators for enhancing environmental efficiency.

On the other hand, Su, Wang, Zhang, and Balezentis (2023) utilized a combination of micro and meso-level data to investigate innovation efficiency, measured through robust frontier methods. They also analyzed the connection between innovation efficiency and various factors, including age, size, technology level, and industrial and regional characteristics. Their study revealed that enterprise characteristics were pivotal in determining innovation efficiency. High-tech businesses and larger business scales were found to have a positive impact on innovation. However, the influence of the business age on innovation efficiency was more complex than previously assumed, displaying a nonlinear effect.

Nonetheless, no studies employed the more reliable production frontier technique to assess company performance while investigating its connections with the organization's motivational schemes, tax payments, and labor intensity. Furthermore, research outcomes highlighting varied influences on performance attributable to organizational practices underscore the significance of country-specific factors and data dimensions in shaping this relationship. In essence, the impact of organizational practices on firm performance can vary significantly depending on the country's specific context.

3. Data and Methodology

This section describes the data and the methodology used in the current empirical analysis. All data were extracted from the Survey of Manufacturing Industries (SMI) conducted by the Bangladesh Bureau of Statistics (BBS) in 2012 and 2019. The choice of inputs and outputs was made to ensure harmonious alignment with the sustainability criterion and data availability. The chosen inputs encompass labor, gross capital, raw material, and fuel costs, while the outputs include Gross Value Added (GVA) and the number of jobs. GVA and the number of employees convey the manufacturing process's profound impact on the economy and society, respectively. Within this context, a company employs resources derived from the economy, society, and environment to manufacture one or more commercial goods – labor was drawn from the social system, gross capital from the economic system, and raw materials and fuel from the environment.

The number of jobs was treated as a social variable in this work because the employment level in a society significantly impacts its social dynamics, shaping the overall well-being and interactions among its members. A feeling of purpose, financial security, and a way to give back to society are all provided by high employment rates, which in turn promote social stability (Holmes, Mccord, Hagen-zanker, Bergh, & Zanker, 2013; Theodore, 2009). Moneymaking work fosters a sense of identity and belonging, promoting the development of social networks within the workplace and the broader society. On the other hand, high unemployment rates can lead to societal problems, including increased crime rates, strained community relationships, and heightened financial stress among those struggling to make ends meet. Additionally, job creation supports skill development and knowledge transfer, playing a pivotal role in shaping a society's social, economic, and political landscape. Given the societal significance of job creation, this study incorporated the number of jobs an enterprise provides into its output space, viewing it as the societal return of the production process. Moreover, this research focused on four organizational strategies that hold paramount significance for production performance, particularly in developing countries like Bangladesh, where these strategies have not yet received adequate attention. A brief description of the variables is presented in Table 1.

All inputs and Gross Value Added (GVA) were measured in the local currency (BDT) at current market prices. The term "jobs offered" refers to the number of active positions within an enterprise. The ratio of labor costs to the sum of labor and gross capital costs determines labor intensity. The remaining three contextual variables – incentives, social security schemes, and tax payments – were also measured in the local currency at current market prices.

Table 1. Descriptive statistics of outputs, inputs, and organizational practices.

Variables	Year	N	Mean	Std. dev.	Min.	Max.
Output variables						
GVA	2012	52	76761543	114700000	2202373	556200000
	2019	52	808700000	2304000000	2433818	15480000000
Jobs offered	2012	52	159	244	13	1329
	2019	52	218	286	14	1058
Input variables						
Total salary	2012	52	19558990	30418307	1258600	156300000
	2019	52	36760138	54349939	1372472	300600000
Gross capital	2012	52	77293838	133900000	195000	688700000
	2019	52	278300000	476400000	279401	2533000000
Raw mat. cost	2012	52	194700000	320300000	2387076	1585000000
	2019	52	261300000	343200000	2386285	1474000000
Fuel cost	2012	52	5410057	9034882	36000	36342768
	2019	52	14236251	23307004	76991	115500000
Contextual variables						
Incentives/GVA	2012	52	0.040	0.030	0.005	0.133
	2019	52	0.010	0.014	0.000	0.076
Social sec./GVA	2012	52	0.002	0.002	0.000	0.011
	2019	52	0.002	0.004	0.000	0.028
Taxes paid /GVA	2012	52	0.053	0.053	0.003	0.262
	2019	52	0.062	0.135	0.000	0.887
Labor intensity	2012	52	0.301	0.174	0.054	0.866
	2019	52	0.263	0.211	0.028	0.939

Consider a production process with p inputs denoted by the vector $X \in \mathbb{R}_+^p$ and q outputs denoted by the vector $\boldsymbol{Y} \in \mathbb{R}_+^q$. The production possibilities set represents the collection of all technically feasible input-output combinations and can be expressed as.

$$\mathcal{P} = \{(x, y) \in \mathbb{R}_+^p \times \mathbb{R}_+^q : x\ can\ produce\ y\} \quad (1)$$

Based on the probabilistic approach of efficiency measurement (Cazals, Florens, & Simar, 2002; Daraio & Simar, 2005, 2007) the set $\mathcal{P}$ corresponds to the support of the q-variate survival functions, $S_{Y|X}(x|y) = Pr(Y \geq y | X \leq x)$, which captures the probability that the output values are at least as high as a given threshold, given the values of the input variables. This probabilistic formulation provides a useful framework for analyzing the efficiency of production processes, as it allows modeling the stochastic nature of the inputs and outputs (Bădin & Daraio, 2012). Using the framework, the Farrell output distances for a production unit operating at (x, y) can be expressed as.

$$\lambda(x,y) \equiv \ sup\{\lambda \mid S_{Y|X}(\lambda y|x) > 0\} \quad (2)$$

Now, the joint probability of finding a unit (X, Y) dominating the point (x, y) can be expressed as $H_{XY}(x,y) = \ Pr(X \leq x,\ Y \geq y)$. Cazals et al. (2002) show that under the free disposability assumption, $\mathcal{P}$ can be expressed in terms of the joint probability distribution $H_{XY}(x,y)$ as follows.

$$\mathcal{P} \equiv \{(x,y) \in \mathbb{R}_+^p \times \mathbb{R}_+^q | \ H_{XY}(x,y) > 0\} \quad (3)$$

In this probabilistic formulation, inputs and outputs can take negative values (Simar & Vanhems, 2012). Radial input and output distance functions can be defined using the support of this probability function. For all $(x,y) \in \mathcal{P}$ such that $S_Y(y) = \ Pr(Y \geq y) > 0$ implies that

$$\theta(x,y) = \ inf\{\theta > 0 | H_{XY}(\theta x, y) > 0\} \quad (4)$$

And similarly, for all $(x,y) \in \mathcal{P}$ such that $F_X(x) = \ Pr(X \leq x) > 0$ entails that

$$\lambda(x,y) \equiv \ sup\{\lambda \ > \ 0 \mid H_{XY}(x, \lambda\, y) > 0\} \quad (5)$$

Using a sample of observations $\{X_i, Y_i, Z_i\}_{i=1}^n$, the nonparametric estimators of $\lambda(x,y)$ can be obtained by plugging in the nonparametric estimator of the corresponding distribution H_{XY}. The empirical version of $H_{XY}(x,y)$ is given by-

$$\widehat{H}_{n,XY}(x,y) = \frac{1}{n}\sum_{i=1}^n \mathbf{1}(\ x \geq X_i, y \leq \ Y_i) \quad (6)$$

Where $1(.)$ is the indicator function [$\mathbf{1}$(a) = 1 if a is true and 0 otherwise].

However, by construction, nonparametric deterministic frontier models are susceptible to extreme values and outliers (Cazals et al., 2002). Cazals et al. (2002) propose an estimation method that is more robust to extreme values, noise, or outliers than the standard DEA or FDH nonparametric estimators. The idea is to define a less extreme boundary as a benchmark, i.e., to define a partial frontier in contrast to the full frontier used above. By design, some data points may lie outside the partial frontier, but the partial frontier provides a helpful benchmark for evaluating efficiency (Daraio, Simar, & Wilson, 2018). They define the concept of the expected minimum input function and expected maximum output function of a subsample of the data to construct the order-m frontier. For a given level of inputs x in the interior of the support of X, consider m i.i.d. random variables $Y_i, i = 1, \dots, m$ generated by the conditional q-variate distribution function $F_Y(y|x) = Prob(Y \geq y | X \leq x)$ and define the set.

$$\mathcal{P}_m(x) = \{(x', y) \in \mathbb{R}_+^{p+q} \mid x' \leq x, Y_i \leq y, i = 1, \dots, m\} \quad (7)$$

Then, for any y, it may be defined as.

$$\begin{aligned} \tilde{\lambda}_m(x,y) &= sup\{\lambda \mid (x, \lambda y) \in \mathcal{P}_m(x)\} \\ &= \max_{i=1,\dots,m}\left\{\min_{j=1,\dots,q}\left(\frac{Y_i^j}{y^j}\right)\right\} \end{aligned} \quad (8)$$

Then, the order-m output efficiency measure for a given integer m ≥ 1 is defined as the expected value of $\tilde{\lambda}_m(x,y)$ over all x in the interior of the support of X.

$$\lambda_m(x,y) = E(\tilde{\lambda}_m(x,y) \mid X \leq x) \quad (9)$$

The previous analysis can be readily extended to situations where external variables $Z \ \in \mathbb{R}_+^r$ are available to provide supplementary information explaining a portion of the production process. The primary approach to integrating this information into the model is to condition the production process on a particular value of $Z = z$.

Consider x be a given level of inputs in the interior of the support of X, and let $Y_i, i = 1, \dots, m$ be m i.i.d. random variables generated by the conditional q-variate distribution function $F_Y(y|x,z) = Prob(Y \geq y | X \leq x, Z = z)$. It is possible to define the set.

$$\mathcal{P}_m^z(x) = \{(x', y) \in \mathbb{R}_+^{p+q} \mid x' \leq x, Y_i \leq y, i = 1, \dots, m\} \quad (10)$$

As the output variables are generated through the function, $F_Y(y|x,z)$, the production set is dependent on Z. When Z takes a specific value z, the conditional survivor of X and Y given $Z = z$ represents the data-generating process that relies on the exogenous environment denoted by Z. Therefore, one can define for any y:

$$\begin{aligned} \tilde{\lambda}_m^z(x,y) &= sup\{\lambda \mid (x, \lambda y) \in \mathcal{P}_m^z(x)\} \\ &= \max_{i=1,\dots,m}\left\{\min_{j=1,\dots,q}\left(\frac{Y_i^j}{y^j}\right)\right\} \end{aligned} \quad (11)$$

The conditional order-m output efficiency measure is given by.

$$\lambda_m(x,y|z) = E(\tilde{\lambda}_m(x,y) \mid X \leq x, Z = z) \quad (12)$$

The conditional order-m frontier $\lambda_m(x,y|z)$ can be derived in a similar fashion where Y are distributed as $S_{Y|X,Z}(y|X \leq x,\ Z = z)$. The nonparametric estimators are obtained by plugging the nonparametric estimators of the survival functions in $\lambda_m(x,y|z)$. If $m \to \infty$, the order-m frontier and its estimators tend to converge to the full frontier. However, the partial frontier will not envelope all the data points for a finite m and thus is more robust than the full frontier (Mastromarco & Simar, 2018). The order-m efficiency scores can take values greater, less, or equal to 1. A DMU having an efficiency score of one lies on the frontier. Values greater than one imply inefficiency, whereas values less than one indicate super-efficiency.

4. Results and Discussions

This paper focuses on assessing the contributions of individual subsectors to creating economic value, considering their input-to-output conversion processes and performance variations over time. Moreover, the study results are presented detailing the effects of organizational practices, including incentives, social security schemes, company tax payments, and labor intensity, on performance heterogeneity at the subsector level. Understanding the technical performance of manufacturing subsectors, their evolving patterns over time, and their response to organizational practices is pivotal for transforming the manufacturing sector into a resilient driver of long-term economic growth. Additionally, by examining the estimated technical efficiency scores, it is possible to identify potential subsectors that can enter foreign currency-earning industries.

Non-parametric efficiency metrics depend on the model specifications, and several estimating frameworks have been proposed in the literature, each having advantages and disadvantages of its own. The output- or input-oriented radial measures are the traditional frontier models based on constant or variable returns to scale. In this research, the technical efficiency scores of various manufacturing subsectors have been computed using two commonly recognized frameworks: The CCR (Charnes, Cooper, and Rhodes) model (Charnes, Cooper, & Rhodes, 1978) and the BCC (Banker, Charnes, and Cooper) model (Banker, Charnes, & Cooper, 1984). While the BCC model is based on variable returns to scale, the CCR model assumes constant returns to scale. The efficiency ratings produced by these two frameworks under restrictive assumptions can be compared with those produced by other frameworks.

The tests of constant returns to scale versus variable returns to scale developed by Kneip, Simar, and Wilson (2016) and Simar and Wilson (2020) were applied to evaluate which returns to scale should fit a frontier model. Setting the number of sample splits to 10 (NSPLIT=10) and using the Simar and Wilson (2020) bootstrap approach of 1000 replications permitted the execution of two tests implemented in the R package FEAR (Wilson, 2008).

The first test uses the mean of test statistics from Kneip et al. (2016) over ten random sample splits. To determine whether the bootstrapped p-values of the test statistics for each sample-split are uniformly distributed, the second test uses a Kolmogorov-Smirnov one-sample test. Table 2 provides an overview of the test results, showing that the 2012 data set demonstrates variable returns to scale (with p-values less than 0.5), whereas the 2019 data set exhibits constant returns to scale (with p-values greater than 0.5). Given that there were different returns to scale alternatives for the two data sets, but common returns to scale are preferable for comparisons, and the recent dataset corresponds to CRS, the current work assumed CRS for measuring technical efficiency scores. Afterward, the validity of the convexity assumption was checked by employing the tests proposed by Kneip et al. (2016) and Simar and Wilson (2020). The procedure involves testing the null hypothesis of convexity against nonconvexity by randomly splitting the sample into two subsamples and then comparing the mean efficiency of the first subsample with the convexity assumption with the mean efficiency of the second subsample, allowing for the nonconvexity of the technology.

Table 2. Test results of returns to scale.

Year	tau1	tau2	Pvalue1	Pvalue2	R.T.S.
2012	4.474	0.978	0.001	0	VRS
2019	1.177	0.611	0.264	0.115	CRS

Using the bootstrap method, two convexity tests were performed with ten multiple splits, which share a testing procedure like the RTS testing described above. The results presented in Table 3 indicate that the convexity assumption holds for both the 2012 and 2019 data sets.

Table 3. Test results of convexity.

Year	tau1	tau2	Pvalue1	Pvalue2	Convexity
2012	NA	0.883	NA	0.253	Convex
2019	0.906	0.460	0.207	0.232	Convex

4.1. Benchmarking DMUs for the Partial Frontier

Full frontier models' efficiency ratings are susceptible to extreme values and outliers, which are frequent in industrial data like ours. As a result, partial frontier-based order-m efficiency ratings have been additionally calculated, which are thought to be more resistant to extreme values and outliers (Cazals et al., 2002). Rather than performing DEA efficiency analysis using the entire sample as a reference, the order-m framework uses artificial reference samples of the size specified by m, randomly drawn with replacement from the peer DMU in the original data. Order-m efficiency scores are estimated as averages of DEA-like efficiency scores drawing the artificial sample repeated 200 times. The procedure has also invoked the bootstrapping of 200 replications.

The reciprocals of the resultant scores obtained from an output-oriented order-m model are efficiency measures and can be used to perceive the performance of the subsectors.

In the robust order-m efficiency measuring approach, determining the number of Decision-Making Units (DMUs) constituting the partial frontier, denoted as m, holds significant importance. A commonly adopted guideline suggests setting m as n2/3, where n represents the original sample size (Luiza Bădin, Daraio, & Simar, 2019). Additionally, Daraio and Simar (2007) and Simar (2003) propose selecting a value form that minimizes the number of points falling outside the efficiency frontier. Experiments were conducted to explore the effects of different m values, with the observed results depicted in Figure 1-Figure 2. The curves gradually approach the full sample size before reaching a plateau. Based on these findings, 'm=50' has been chosen for the 2012 and 2019 datasets.

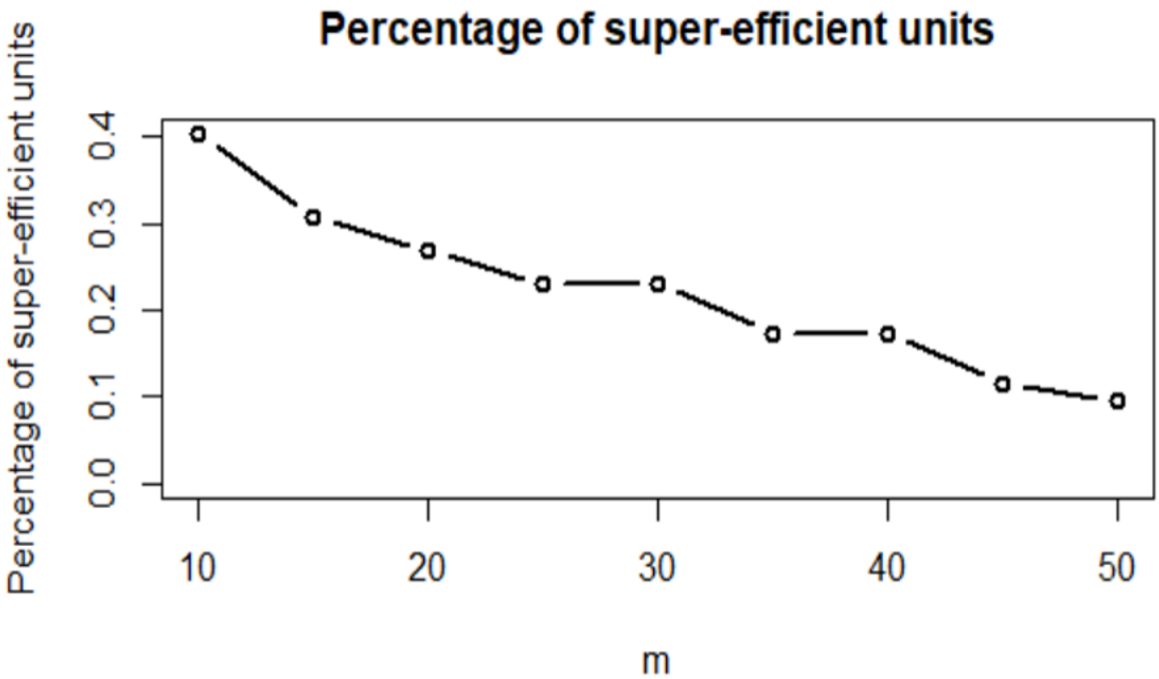

Figure 1. Percentage of super-efficient DMUs as the value of m changes: 2012.

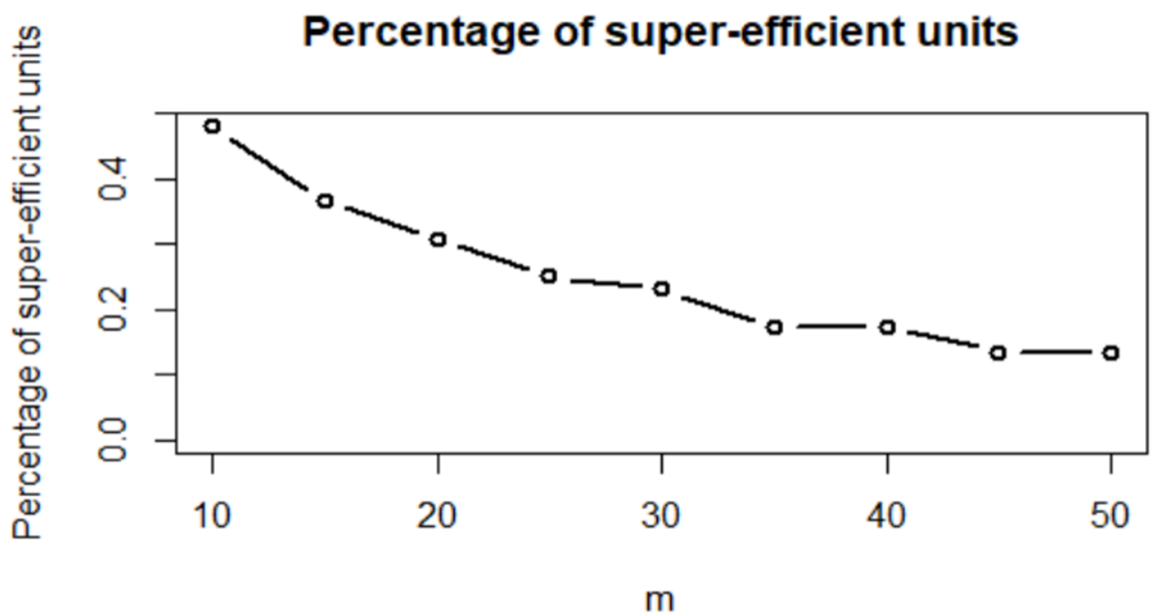

Figure 2. Percentage of super-efficient DMUs as the value of m changes: 2019.

4.2. Performance Metrics of Manufacturing Subsectors

Table 4 describes the basic statistics of the estimated efficiency scores obtained from CCR, BCC, and order-m models based on output orientation. Original scores were transformed so that greater numbers in the reported scores indicate better efficiency; any score of one indicates that the subsector is on the frontier.

Conversely, a DMU may be outside the frontier in the case of a robust version, which indicates super efficiency with a score higher than one.

The usual explanation for the efficiency scores of the three frameworks is that they reflect the largest radial expansion of outputs that can be reasonably expected from a unit working at (x,y) to achieve the efficiency boundary.

Under constant returns to scale, the mean technical efficiency of Bangladesh's manufacturing subdomains stood at 0.887 in 2012 and 0.625 in 2019. Hence, in 2012, the manufacturing sector attained an average value generation rate of 88.7% of its highest capacity. However, this metric substantially declined, plummeting to 62.5% by 2019, implying a production capacity underutilization of 37.5%. These calculations closely align with the values reported by Samad and Patwary (2002). The count of efficient subsectors was 14 in 2012 and 7 in 2019, respectively. In contrast to 2019, where the minimal efficiency score amounted to 0.213 and a standard deviation of 0.204, the minimum efficiency score in 2012 was 0.654, with a standard deviation of 0.1. These observations indicate a heightened divergence in the overall technical performance in 2019, amplifying the efficiency disparity between subdomains that perform excellently and those that fall behind.

Table 4. Descriptive statistics of technical efficiency scores.

Year	Score	N	Mean	SD	Min	Max
2012	TE_CCR	52	0.887	0.1	0.654	1
	TE_BCC	52	0.975	0.039	0.846	1
	TE_Robust	52	1.023	0.065	0.895	1.31
2019	TE_CCR	52	0.625	0.204	0.213	1
	TE_BCC	52	0.81	0.18	0.389	1
	TE_Robust	52	.895	0.18	0.419	1.329

The efficiency series derived from the BCC and robust models depict a nearly identical scenario. Table 4 provides evidence that both the average and lowest efficiency scores experienced a decline in 2019, accompanied by a higher standard deviation compared to 2012 across the three variations of frontier models. The shift in efficiency scores and the changing distribution patterns depicted in Figure 3 paint a complex picture of the manufacturing sector's evolution. These shifts drag the average scores down, signifying a noted decline in overall efficiency levels across the manufacturing sector during this period. In 2012, the distributions exhibited high peaks, indicating that certain subsectors within manufacturing demonstrated exceptionally high levels of efficiency. However, by 2019, these peaks diminished, suggesting that the sectors that previously exhibited outstanding performance in 2012 had experienced a decline in their efficiency levels. This decline could be attributed to various factors, such as changes in market dynamics, technological disruptions, or adjustments in consumer preferences, impacting specific subsectors more severely than others.

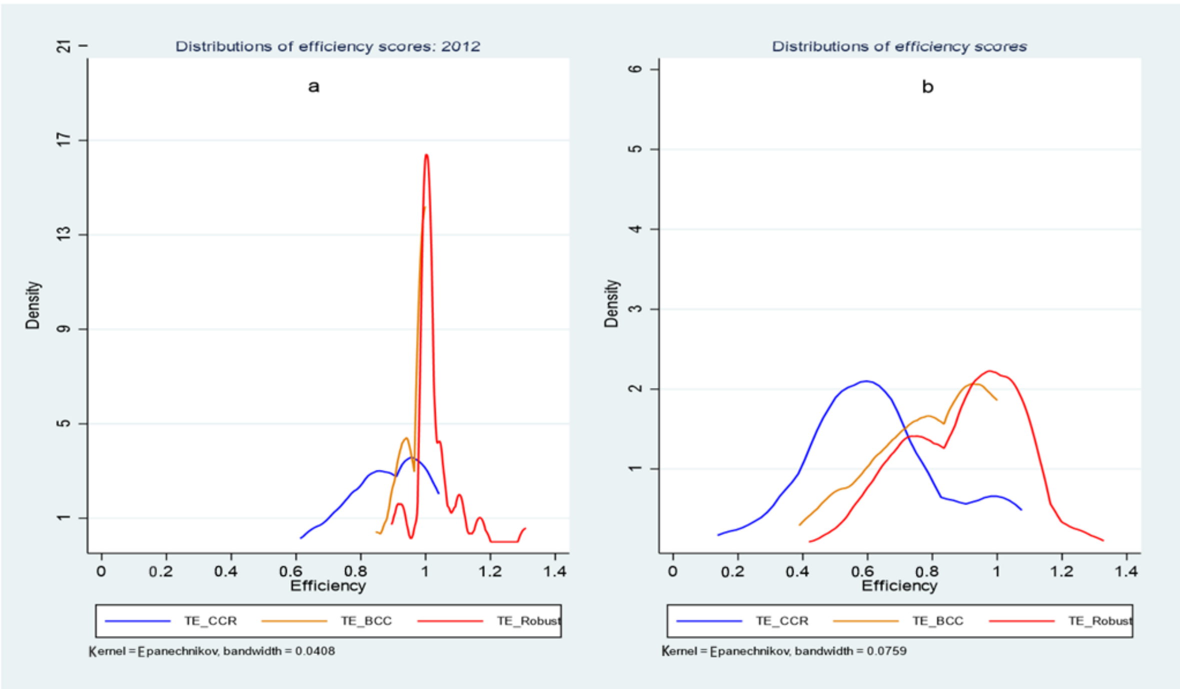

Figure 3. Distributions of technical efficiency scores.

Furthermore, the broader spread of curves observed in 2019 indicates an intensified heterogeneity among manufacturing outcomes. Unlike the more clustered and narrower distribution in 2012, the increased variability in 2019 suggests a greater disparity in efficiency levels across different manufacturing subsectors. A number of causes, such as different responses to technology improvements, inequalities in resource allocation, and variations in organizational practices among firms, can be responsible for this increased heterogeneity.

Given the variations in production technologies, it is essential to note that the lower average efficiency across all categories in 2019 does not necessarily imply a decline in performance across all subsectors. A closer examination discovered that seven subsectors positioned on the efficiency frontiers in 2012 became inefficient by 2019, as indicated by all frontier models. These subsectors included the manufacture of luggage, handbags, and similar items; saddlery and harness manufacturing; the manufacture of wooden containers; printing; service activities related to printing; the manufacture of cement, lime, and plaster; the casting of non-ferrous metals and manufacturing parts and accessories for motor vehicles all lost its efficiency status in 2019.

Conversely, in three measures of efficiency, four subsectors that exhibited inefficiency in 2012 successfully transitioned into efficient ones in 2019. These noteworthy subsectors encompassed the manufacture of cocoa, chocolate, and sugar confectionery; the pressing and belling of jute and other fibers; the manufacturing of other textiles n.e.c. (goods designer); and the production of polythene products. Furthermore, three subsectors, namely tobacco manufacturing n.e.c., handloom textile manufacturing, and brick/block/tile manufacturing, managed to maintain their efficiency status throughout both years.

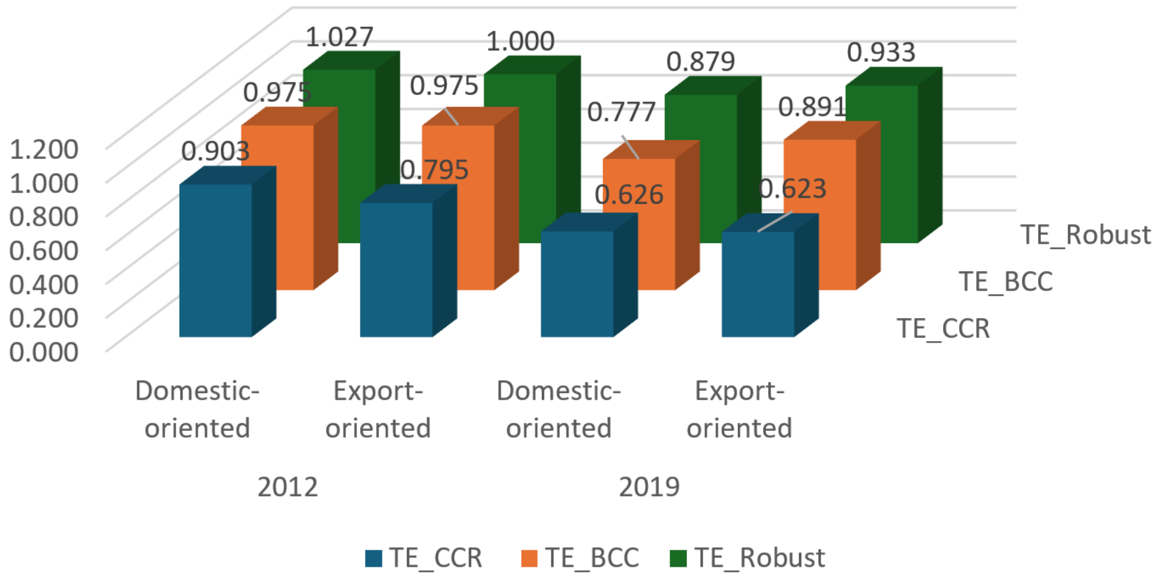

Figure 4. Technical efficiency scores by subsectors' export-orientation.

An examination of efficiency dynamics was undertaken based on the export orientation of subsectors. Subsectors were classified as export-oriented if their overseas sales surpassed domestic market sales. Figure 4 illustrates the evolving pattern of technical efficiency in relation to export orientation.

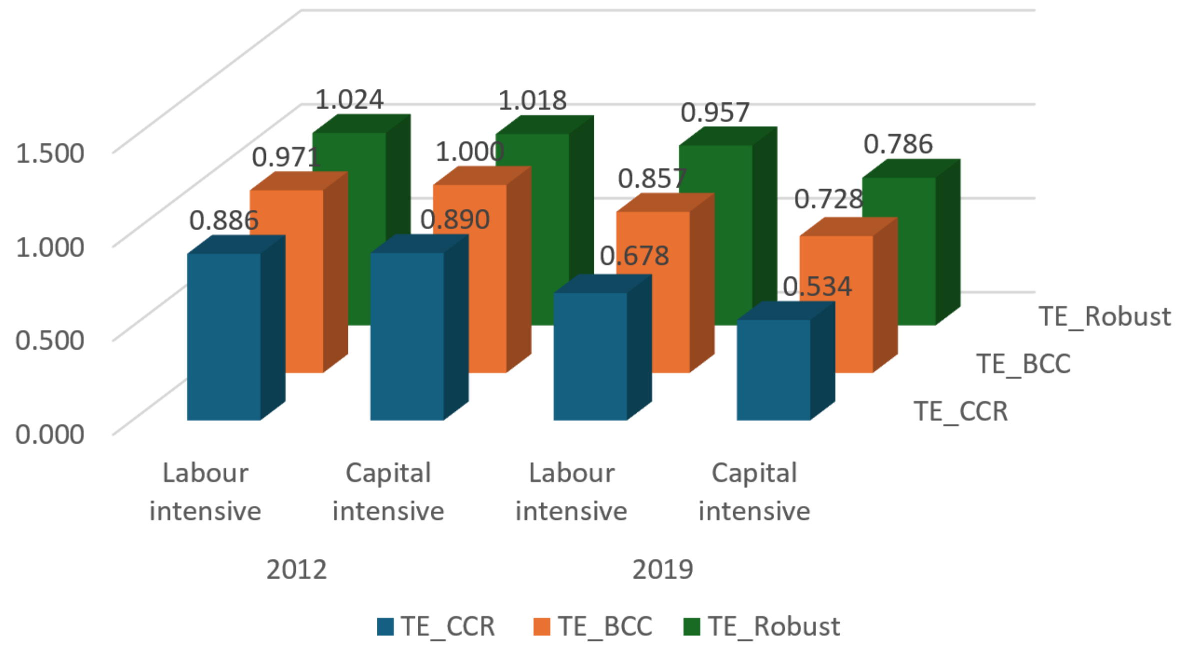

Figure 5. Technical efficiency by subsectors' capital intensity.

The bar chart reveals that in 2012, as suggested by all estimated models, export-oriented industries lagged their non-export-oriented counterparts. However, in 2019, a notable shift occurred, with both the BCC and order-m estimates indicating that export-oriented industries had transformed into better-performing subsectors. Capital intensity serves as another critical parameter for evaluating performance dynamics. Given the absence of a universal guideline for designating an industry as capital-intensive, the top 25% of subsectors with the highest capital usage were classified as capital-intensive. The mean technical efficiency scores from the three estimated models indicate that in 2012, capital-intensive subsectors outperformed their counterparts (Figure 5). However, the situation was reversed by 2019, leading capital-intensive industries to experience a decline in performance.

4.3. Organizational Practices' Effect Analysis

The next step in this study was to examine how organizational practices influence manufacturing performance. To do this, the ratio of the estimated conditional order-m robust efficiency scores over the unconditional ones was estimated following Bădin and Daraio (2012). Descriptive statistics of the estimated conditional and unconditional robust efficiency scores are presented in Table 5. The reported efficiency scores were estimated from an output-oriented partial frontier model with the same trimming value used in the previous section (m=50), which implies inefficiency for higher values.

Given that m is very high, the behavior of the ratio between conditional and unconditional efficiency would imply contextual variables' effects on the efficiency frontier. According to Table 5, the overall mean inefficiency of subsectors increased in 2012 with the inclusion of contextual variables' information in the conditional model and fell in 2019, though the differences were not notable. A low difference between conditional and unconditional efficiency can occur when the contextual variables have little influence on the efficiency scores.

Table 5. Basic statistics of conditional and unconditional robust inefficiency scores.

Year	Model	N	Mean	SD	Min	Max
2012	Unconditional	52	0.981	0.057	0.763	1.118
	Conditional	52	1.001	0.008	1.000	1.060
2019	Unconditional	52	1.172	0.289	0.752	2.388
	Conditional	52	1.109	0.209	0.994	2.028

Subsequently, the ratios Q_m defined by the equation **Error! Reference source not found.**were examined to find which organizational practices affect the distribution of inefficiency scores. The ratios could be either ≤ 1 or ≥ 1, depending on the actual effect of Z on the distribution of outputs for the conditional values of inputs. Local linear non-parametric regression models were used to trace the impact of contextual variables on technical efficiency.

A local linear smoothing was applied to trace the impact of contextual variables on production efficiency. Figure 6 to Figure 9 illustrate the estimated ratios' responses to four contextual variables for 2012 and 2019.

In an output orientation, an upward trend of the non-parametric smoothed line suggests a favorable effect of the contextual variable on efficiency. In that case, the contextual variables act like inputs in the production process and help original inputs produce more outputs. In contrast, a downward non-parametric smoothed line signals the contextual variable's unfavorable influence on efficiency. In that case, unfavorable contextual variables create extra pressure in the production process and penalize producing the outputs of interest.

While incentives had essentially no impact on efficiency in 2012, a negative correlation between the two was discernible in 2019. A few extreme observations about incentives largely formed 2019's negative correlation. The data reveals that the incentive levels across various subsectors in Bangladesh were consistently low. Surprisingly, export-oriented industries received a lower percentage of incentives relative to their GVA compared to domestic-oriented industries, both in 2012 and 2019. Similarly, capital-intensive industries exhibited lower incentive margins relative to GVA than non-capital-intensive industries in both years.

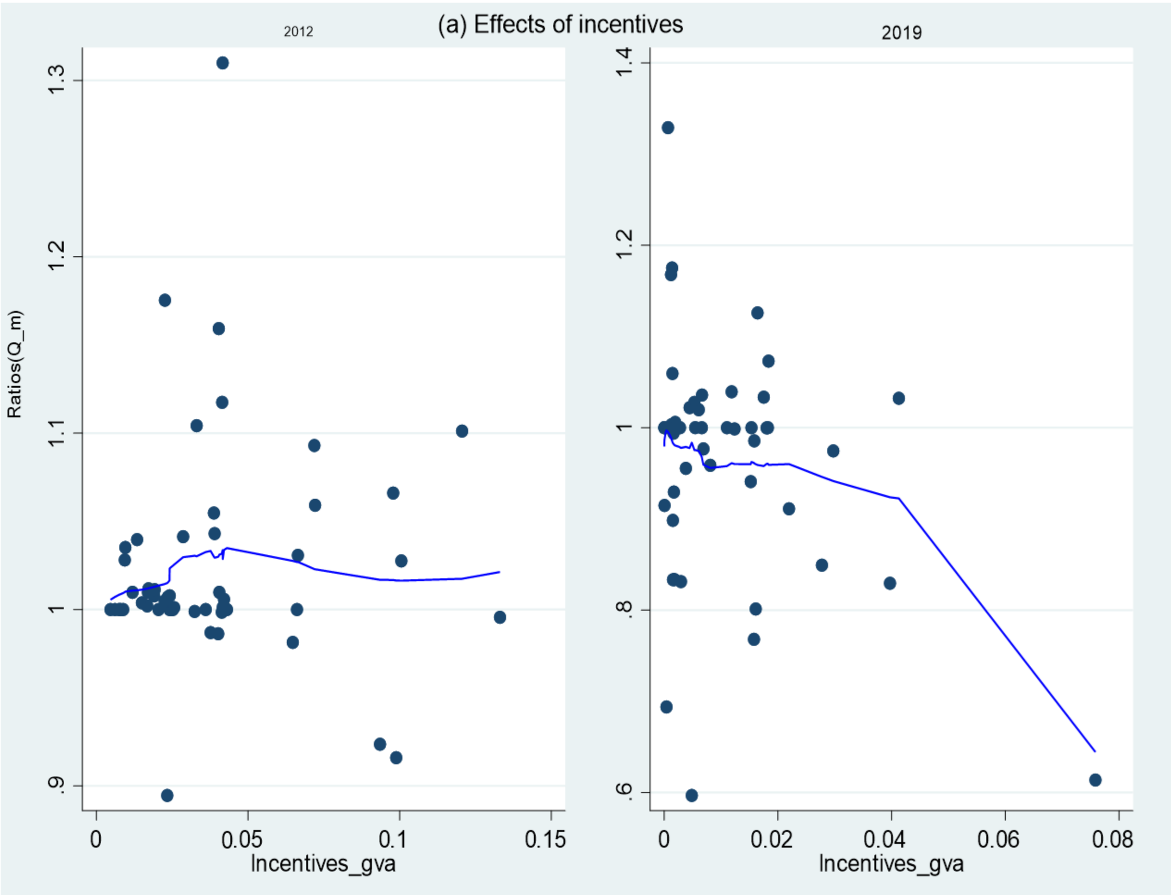

Figure 6. Effects of incentives on the ratios.

These findings imply that while incentives are a common tool to promote economic growth and investment, their effectiveness may be limited in Bangladesh. It suggests that businesses in the country might not fully capitalize on the incentive programs available. In some cases, the data even hints at the possibility that incentive schemes could hinder rather than facilitate the production of goods. Furthermore, the patterns observed in social security schemes mirrored those of incentives, reinforcing that there might be room for improvement in how these support mechanisms are implemented and utilized by businesses in Bangladesh.

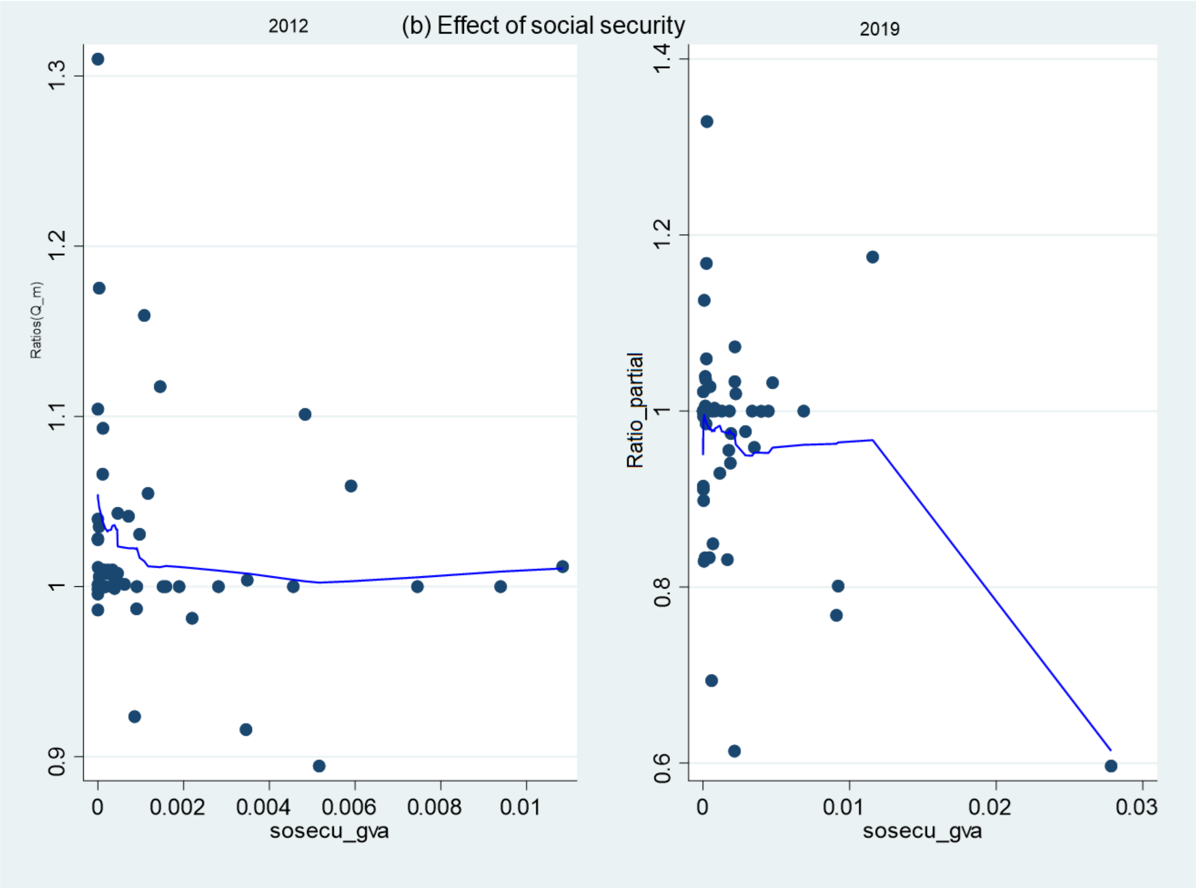

Figure 7. Effects of social security on the ratios.

The structure of the connection between ratios and the social security scheme in both years was shaped by a handful of exceptional data values. Like incentives, social security programs for employees imposed an additional strain on the manufacturing process, leading to a decline in efficiency. Consequently, contrary to the assertions of many authors, such as Lazear (2000); Bloom and Van Reenen (2007); Gomez-Mejia and Welbourne (1988); Heinrich and Marschke (2010); Jones (2010) and Paul and Anantharaman (2003) the reported findings fail to validate the positive correlation between worker welfare programs and organizational performance in Bangladeshi manufacturing data. Instead, the results align with the stance of some other authors (Aschenbrücker & Kretschmer, 2022; Odiri & Ideh, 2021) supporting a negative relationship between workers' welfare schemes and organizational performance.

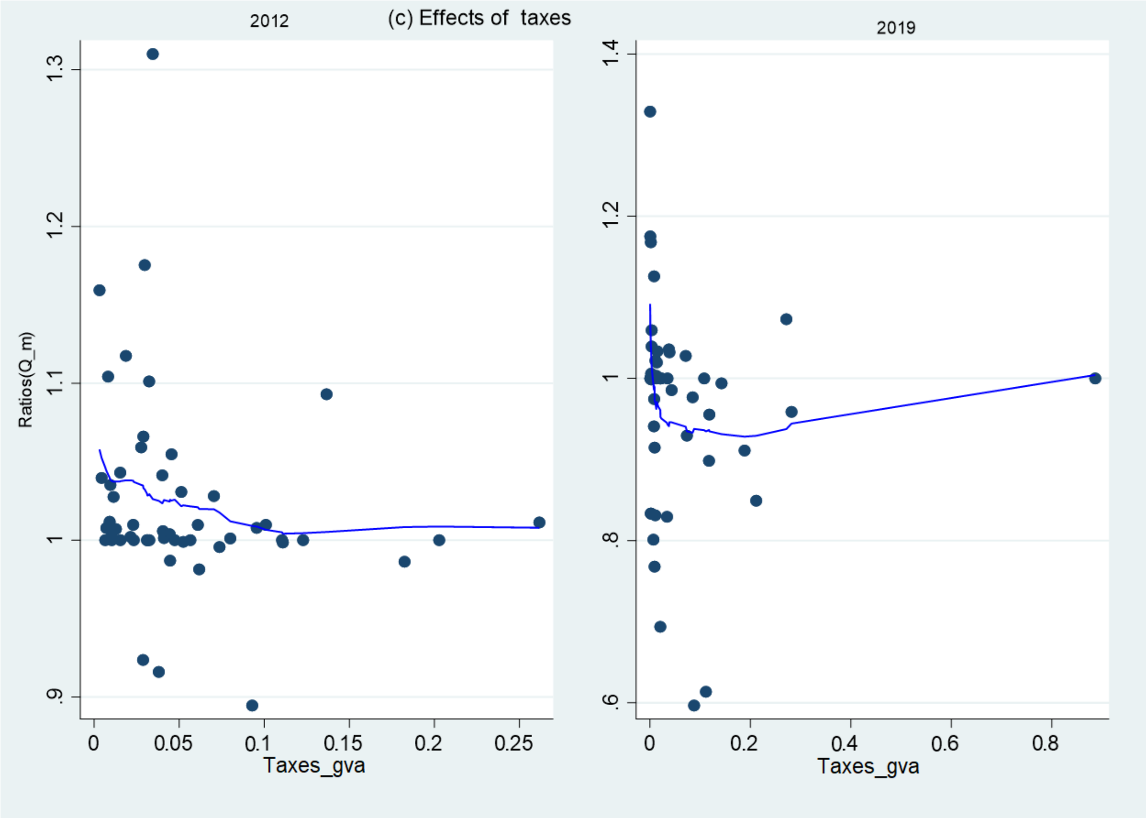

Figure 8. Effects of taxes on the ratios.

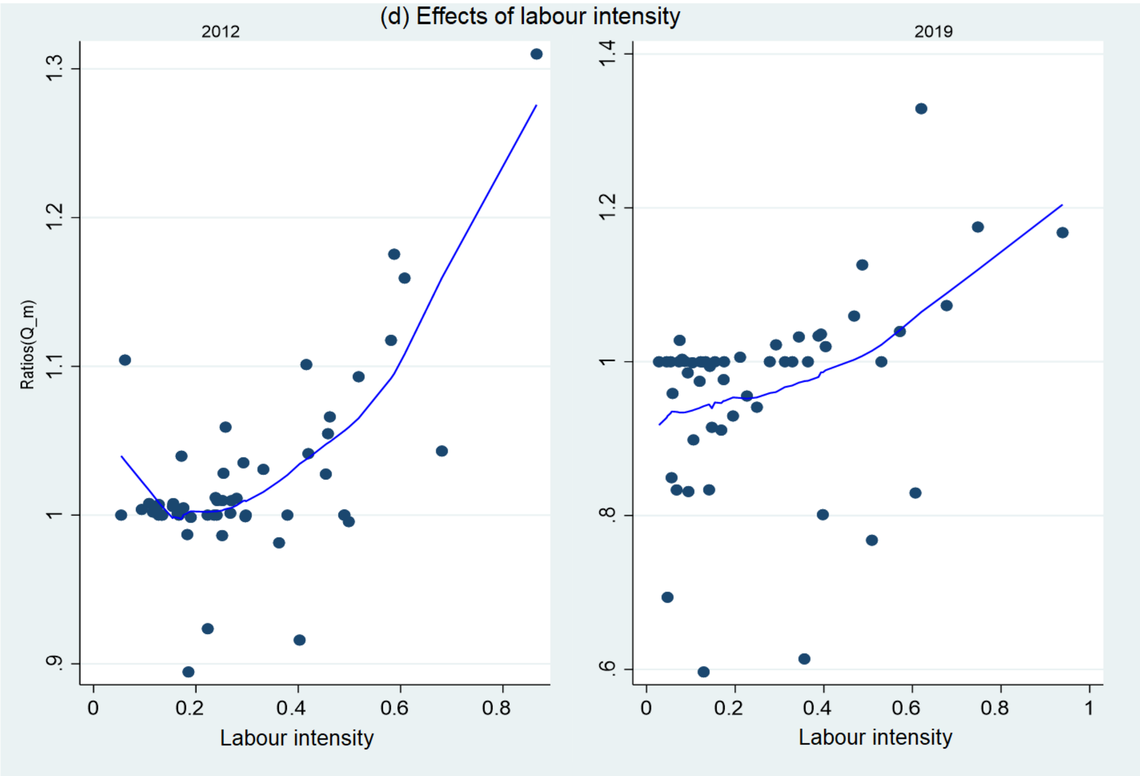

Figure 9. Effects of labor intensity on the ratios.

Table 6. Local linear regression results.

Variables	2012	2019
Incentives_gva	-0.375 (0.293)	-3.677** (1.644)
Sosecu_gva	-1.843 (3.432)	-11.46* (5.960)
Taxes_gva	-0.159 (0.116)	0.023 (0.108)
Labor intensity	0.211*** (0.064)	0.292*** (0.083)
Observations	52	52
R-squared	0.578	0.484

Note: Standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

The disbursement of corporate taxes exhibited disparate trends in 2012 and 2019. As per the data from 2012, subsectors that pay larger amounts in taxes demonstrated diminished efficiency. Conversely, tax payment shows a favorable correlation with production proficiency in 2019. Moreover, a steady positive influence of labor intensity remained throughout both study periods on the manufacturing domain's performance. This result contradicts what Lazăr (2016) found for Romanian firms.

The significance levels of organizational practices on technical performance are depicted in Table 6 through the results of local linear regression models with least squares cross-validation for bandwidth selection. As per the Table, the adverse impacts of incentives and social security schemes were statistically significant in the 2019 dataset, whereas they lacked significance in the 2012 dataset. Taxes, on the other hand, did not exhibit significance in either year. Notably, labor intensity demonstrated high significance in both datasets for the respective years.

5. Conclusions and Policy Implications

This study investigated the technical performance of manufacturing in Bangladesh, focusing on measurement, dependence, and responses to policy changes to identify the root causes of the manufacturing sector's limited contribution to building a solid industrial base for Bangladesh's long-term growth.

According to the SDG 9 index analytics, Bangladesh's manufacturing should improve its productivity performance to become more competitive in the world market, which is essential to leverage long-term economic growth in the changing global scenarios. However, no study has examined how Bangladeshi manufacturing performs economically or how its behavior relates to organizational and regulatory factors at the sub-sectoral level. This study closes the gap. It offers substantial empirical findings that can be helpful to industrial planners and policymakers to strengthen the manufacturing sector and sustain economic growth for a considerable amount of time.

Different frameworks, such as the CCR and BCC models, were utilized to calculate efficiency ratings. In addition, partial frontier-based order-m models were employed to mitigate the impact of extreme values and outliers. The efficiency scores obtained from these models were analyzed and compared, revealing changes in technical performance between 2012 and 2019. This paper further examined the performance of specific subsectors, identified industries with potential for economic growth, and evaluated external factors' influence on efficiency.

Previous studies on productive efficiency in Bangladesh considered only measurement without considering multiple outputs and how manufacturing performance interacts with organizational features and practices. This work represents a significant step toward addressing the existing research gap, standing as the foundational study that evaluates the production performance of Bangladesh's manufacturing sector while simultaneously examining their connections with various organizational practices and characteristics.

According to the results, the manufacturing performance in 2019 exhibited a heightened disparity across subsectors compared to 2012, with some subsectors improving their efficiency while others experiencing a decline. Subsectors that generated export revenue displayed unsatisfactory performance, highlighting the need for organizational improvement. Organizational practices were identified as having a modest impact on manufacturing performance. Subsectors characterized by higher levels of labor intensity demonstrated significantly superior production performance compared to other subsectors.

The analytical results indicate that Bangladesh's manufacturing subdomains experienced significant efficiency changes between 2012 and 2019. Mean technical efficiency scores measured by nonparametric frontier methods dropped from 88.70% to 62.50%, with the number of efficient subsectors decreasing from 14 to 7. The average efficiency scores exhibited similarity to those derived by Samad and Patwary (2002). A heightened disparity in 2019's technical performance amplified the efficiency gap between subsectors. Some previously efficient subsectors like luggage, printing, and cement lost efficiency. Conversely, subsectors like cocoa and textiles improved.

In 2012, service activities related to printing excelled, while textile weaving performed poorly. In 2019, pulp and paper manufacturing ranked at the top. Apparel manufacturing, the key export-oriented industry, improved its ranking from 49th to 11th in 2019, but leather declined.

While export-oriented subsectors benefit from cheap labor and government support, findings suggest their underperformance compared to other industries. Improved resource use and production are required to increase competitiveness. Targeted governmental assistance for export-oriented businesses like garments, footwear, and leather products may also be considered.

Analytical indicators suggest that specific manufacturing sectors, including jute-related industries, the production of cocoa, chocolate, and sugar confectionery, as well as the manufacturing of polythene products, have demonstrated commendable performance in recent times. Given the capabilities of these industries, their products could be incentivised to engage in global market competition. Thus, the analysis identifies the dynamic performance pattern and potential industries that may contribute to upholding the manufacturing sector.

According to the industry-level findings, employee incentives did not influence efficiency in 2012, but a negative correlation developed in 2019, suggesting they might thwart production. Similar patterns are evident with social security programs, collectively implying the ineffectiveness of worker welfare programs to organizational performance. These findings are consistent with the findings of certain studies (Aschenbrücker & Kretschmer, 2022; Odiri & Ideh, 2021). A shift in corporate tax trends has occurred, with higher tax payments suggesting diminished efficiency in 2012 but a favorable correlation in 2019. Tax payment's negative correlation with performance in 2012 is in line with the findings of Schwellnus and Arnold (2008); Lazăr and Istrate (2018) and Belotti et al. (2016). Conversely, labor intensity consistently exerted a positive influence on manufacturing performance, contrary to Lazăr (2016) observations for Romanian business firms.

In short, the findings of this research portray the performance dynamics of Bangladesh's manufacturing sector from 2012 to 2019. During this timeframe, the sector witnessed an overall performance decline while experiencing an increased disparity among industries. This suggests a concerning lack of sustainability in the country's manufacturing production. Among the various industries, the apparel sector, despite being the country's leading industry, exhibited subpar performance compared to jute, chocolate, and polythene manufacturers.

To broaden foreign currency earnings, emphasis should shift to adjacent industries with earnings and diversification potential. The findings highlight satisfactory recent performance and potential for improvement in jute-related industries, cocoa and confectionery production, and polythene manufacturing. While these subsectors have exhibited satisfactory performance, their true potential for growth and competitiveness on the international stage remains largely untapped. To fully harness their export capability, tailored support mechanisms must be implemented.

References

Alvarez, R., & Crespi, G. (2003). Determinants of technical efficiency in small firms. *Small business economics*, *20*, 233-244.

Aschenbrücker, K., & Kretschmer, T. (2022). Performance-based incentives and innovative activity in small firms: Evidence from German manufacturing. *Journal of Organization Design*, *11*(2), 47-64. https://doi.org/10.1007/s41469-022-00124-8

Bădin, L., & Daraio, C. (2012). Explaining efficiency in nonparametric frontier models: Recent developments in statistical inference. *Exploring Research Frontiers in Contemporary Statistics and Econometrics*, 151–175. https://doi.org/10.1007/978-3-7908-2349-3

Bădin, L., Daraio, C., & Simar, L. (2019). A bootstrap approach for bandwidth selection in estimating conditional efficiency measures. *European Journal of Operational Research*, *277*(2), 784-797. https://doi.org/10.1016/j.ejor.2019.02.054

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management science*, *30*(9), 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Banker, R. D., & Natarajan, R. (2008). Evaluating contextual using data variables envelopment affecting analysis. *Operations Research*, *56*(1), 48-58. https://doi.org/10.1287/opre.l070.0460

Baten, A., Rana, M., Das, S., & Nesa, M. K. (2007). Privatization and regional agglomeration effect on technical efficiency of Bangladesh manufacturing industry. *Journal of Economic Cooperation among Islamic countries*, *28*(4), 81–104.

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. *The Lahore Journal of Economics*, *11*(2), 23-41. https://doi.org/10.35536/lje.2006.v11.i2.a2

Belotti, F., Di Porto, E., & Santoni, G. (2016). *The effect of local taxes on firm performance: Evidence from geo-referenced data.* Uppsala University, Department of Economics, Working Paper Series No. 2016:3.

Bhandari, A. K., & Ray, S. C. (2012). Technical efficiency in the Indian textiles industry: A non-parametric analysis of firm-level data. *Bulletin of Economic Research*, *64*(1), 109-124. https://doi.org/10.1111/j.1467-8586.2010.00381.x

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, *122*(4), 1351-1408.

Bregn, K. (2013). Detrimental effects of performance-related pay in the public sector? On the need for a broader theoretical perspective. *Public Organization Review, 13*, 21-35. https://doi.org/10.1007/s11115-012-0191-x

Bryson, A., & Forth, J. (2018). The impact of management practices on SME performance. *National Institute of Economic and Social Research, 488*.

Camilleri, M. A. (2017). Corporate sustainability, social responsibility and environmental management. *Corporate Sustainability, Social Responsibility and Environmental Management*. https://doi.org/10.1007/978-3-319-46849-5

Cazals, C., Florens, J.-P., & Simar, L. (2002). Nonparametric frontier estimation: A robust approach. *Journal of econometrics, 106*(1), 1-25. https://doi.org/10.1016/S0304-4076(01)00080-X

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chen, C.-M., & Delmas, M. A. (2012). Measuring eco-inefficiency: A new frontier approach. *Operations Research, 60*(5), 1064-1079. https://doi.org/10.1287/opre.1120.1094

Dalei, N. N., & Joshi, J. M. (2020). Estimating technical efficiency of petroleum refineries using DEA and tobit model: An India perspective. *Computers & Chemical Engineering, 142*, 107047. https://doi.org/10.1016/j.compchemeng.2020.107047

Daraio, C., & Simar, L. (2005). Introducing environmental variables in nonparametric frontier models: A probabilistic approach. *Journal of Productivity Analysis, 24*, 93-121.

Daraio, C., & Simar, L. (2007). Conditional nonparametric frontier models for convex and nonconvex technologies: A unifying approach. *Journal of Productivity Analysis, 28*, 13-32. https://doi.org/10.1007/s11123-007-0049-3

Daraio, C., Simar, L., & Wilson, P. W. (2018). Central limit theorems for conditional efficiency measures and tests of the 'separability'condition in non-parametric, two-stage models of production. *The Econometrics Journal, 21*(2), 170-191. https://doi.org/10.1111/ectj.12103

Furubotn, E. G., & Richter, R. (2005). *Institutions and economic theory: The contribution of the new institutional economics* (2nd ed.). Ann Arbor, MI: University of Michigan Press.

Gatsi, J. G., Gadzo, S. G., & Kportorgbi, H. K. (2013). The effect of corporate income tax on financial performance of listed manufacturing firms in Ghana. *Research Journal of Finance and Accounting, 4*(15), 118-124.

General Economics Division. (2012). *Perspective plan of Bangladesh 2010–2021: Making vision 2021 a reality*. Dhaka: Planning Commission, Government of the People's Republic of Bangladesh.

Gomez-Mejia, L. R., & Welbourne, T. M. (1988). Compensation strategy: An overview and future steps. *Human Resource Planning, 11*(3), 173-189.

Gu, Y., Nayyar, G., & Sharma, S. (2021). *Gearing up for the future of manufacturing in Bangladesh*: World Bank. https://doi.org/10.1596/35879.

Halkos, G. E., & Tzeremes, N. G. (2010). The effect of foreign ownership on SMEs performance: An efficiency analysis perspective. *Journal of Productivity Analysis, 34*, 167-180. https://doi.org/10.1007/s11123-010-0174-2

Heinrich, C. J., & Marschke, G. (2010). Incentives and their dynamics in public sector performance management systems. *Journal of Policy Analysis and Management, 29*(1), 183-208. https://doi.org/10.1002/pam.20484

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. *European Journal of Operational Research, 181*(1), 425-435. https://doi.org/10.1016/j.ejor.2006.05.019

Holmes, R., Mccord, A., Hagen-zanker, J., Bergh, G., & Zanker, F. (2013). *What is the evidence on the impact of employment creation on stability and poverty reduction in fragile states A systematic review (Issue May)*. London: Overseas Development Institute.

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

İlleez, A. A., & Güner, M. (2018). Applications of data envelopment analysis in textile sector. *International Journal of Multidisciplinary Studies and Innovative Technologies, 2*(2), 72-75.

Jones, C. (2010). Exploring new ways of assessing the effect of regulation on environmental management. *Journal of Cleaner Production, 18*(13), 1229-1250. https://doi.org/10.1016/j.jclepro.2010.04.007

Jones, D. C., Kalmi, P., & Kauhanen, A. (2010). Teams, incentive pay, and productive efficiency: Evidence from a food-processing plant. *ILR Review, 63*(4), 606-626. https://doi.org/10.1177/001979391006300403

Joshi, R., & Singh, S. P. (2012). Technical efficiency and its determinants in the Indian garment industry. *Journal of the Textile Institute, 103*(3), 231-243. https://doi.org/10.1080/00405000.2011.564797

Kneip, A., Simar, L., & Wilson, P. W. (2016). Testing hypotheses in nonparametric models of production. *Journal of Business & Economic Statistics, 34*(3), 435-456. https://doi.org/10.1080/07350015.2015.1049747

Krishna, K., & Sahota, G. S. (1991). Technical efficiency in Bangladesh manufacturing industries. *The Bangladesh Development Studies, 19*(1), 89-105.

Kumar, S., & Dua, P. (2022). Environmental management practices and financial performance: Evidence from large listed Indian enterprises. *Journal of Environmental Planning and Management, 65*(1), 37-61. https://doi.org/10.1080/09640568.2021.1877641

Lazăr, S. (2016). Determinants of firm performance: evidence from Romanian listed companies. *Review of Economic and Business Studies, 9*(1), 53-69. https://doi.org/10.1515/rebs-2016-0025

Lazăr, S., & Istrate, C. (2018). Corporate tax-mix and firm performance. A comprehensive assessment for Romanian listed companies. *Economic Research-Ekonomska istraživanja, 31*(1), 1258-1272. https://doi.org/10.1080/1331677X.2018.1482225

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review, 90*(5), 1346-1361. https://doi.org/10.1257/aer.90.5.1346

Leibenstein, H. (1966). Allocative efficiency vs." X-efficiency". *The American Economic Review, 56*(3), 392-415.

Maes, J., Sels, L., & Roodhooft, F. (2005). Modelling the link between management practices and financial performance. Evidence from small construction companies. *Small Business Economics, 25*, 17-34. https://doi.org/10.1007/s11187-005-4255-y

Martin, R., Muûls, M., De Preux, L. B., & Wagner, U. J. (2012). Anatomy of a paradox: Management practices, organizational structure and energy efficiency. *Journal of Environmental Economics and Management, 63*(2), 208-223. https://doi.org/10.1016/j.jeem.2011.08.003

Mastromarco, C., & Simar, L. (2018). Globalization and productivity: A robust nonparametric world frontier analysis. *Economic Modelling, 69*, 134-149. https://doi.org/10.1016/j.econmod.2017.09.015

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses. *European Journal of Operational Research, 197*(2), 792-798. https://doi.org/10.1016/j.ejor.2008.07.039

Nath, N. C. (2021). *Manufacturing sector of Bangladesh-growth, structure and strategies for future development.* Paper presented at the Bienn Conf "Global Econ Vis.

Odiri, V., & Ideh, A. (2021). Determinants of organizational performance in Nigeria: Evidence from service firms. *Humanities and Social Sciences Letters, 9*(1), 86-95. https://doi.org/10.18488/JOURNAL.73.2021.91.86.95

Park, J. (2022). What makes performance-related pay effective in the public sector? Target, pay design, and context. *Review of Public Personnel Administration, 42*(3), 416-443. https://doi.org/10.1177/0734371X21990722

Paul, A. K., & Anantharaman, R. N. (2003). Impact of people management practices on organizational performance: Analysis of a causal model. *The International Journal of Human Resource Management, 14*(7), 1246-1266. https://doi.org/10.1080/0958519032000145648

Pitulice, I., Stefanescu, A., Minzu, V., Popa, A., & Niculescu, A. (2016). Research of corporate tax impact on financial performance. Case of companies listed on Bucharest Stock Exchange. *Management and Economics Review, 1*(2), 203-216.

Ramalho, E. A., Ramalho, J. J., & Henriques, P. D. (2010). Fractional regression models for second stage DEA efficiency analyses. *Journal of Productivity Analysis, 34*, 239-255. https://doi.org/10.1007/s11123-010-0184-0

Rashid, M. H. U., Zobair, S. A. M., Shadek, M. J., Hoque, M. A., & Ahmad, A. (2019). Factors influencing green performance in manufacturing industries. *International Journal of Financial Research, 10*(6), 159-173.

Rodriki, D. (2007). *Industrial development: Some stylized facts and policy directions.* Industrial Development for the 21st Century: Sustainable Development Perspectives (pp. 7–28). Department of Economic and Social Affairs , UN.

Roudaut, N., & Vanhems, A. (2012). Explaining firms efficiency in the Ivorian manufacturing sector: A robust nonparametric approach. *Journal of Productivity Analysis, 37*, 155-169. https://doi.org/10.1007/s11123-011-0227-1

Roy, S., Das, M., Ali, S. M., Raihan, A. S., Paul, S. K., & Kabir, G. (2020). Evaluating strategies for environmental sustainability in a supply chain of an emerging economy. *Journal of Cleaner Production, 262*, 121389. https://doi.org/10.1016/j.jclepro.2020.121389

Samad, Q. A., & Patwary, F. K. (2002). Technical efficiency and technical change in the major manufacturing industries of Bangladesh. *Bangladesh Development Studies, 28*(1/2), 113–135. https://doi.org/10.1155/2014/376486

Sarkis, J. (2016). Corporate environmental sustainability and DEA. In *Handbook of Operations Analytics Using Data Envelopment Analysis* (pp. 483-498). Boston, MA: Springer.

Schwellnus, C., & Arnold, J. (2008). Do corporate taxes reduce productivity and investment at the firm level? Cross-Country evidence from the amadeus dataset. *Structure, 641*, 1–26.

Siebers, P.-O., Aickelin, U., Battisti, G., Celia, H., Clegg, C., Fu, X., . . . Adriano, P. (2008). *The role of management practices in closing the productivity gap (Issue February 2008, pp. 1–29).* Retrieved from http://arxiv.org/abs/0803.2995

Simar, L. (2003). Detecting outliers in frontier models: A simple approach. *Journal of Productivity Analysis, 20*, 391-424. https://doi.org/10.1023/A:1027308001925

Simar, L., & Vanhems, A. (2012). Probabilistic characterization of directional distances and their robust versions. *Journal of Econometrics, 166*(2), 342-354. https://doi.org/10.1016/j.jeconom.2011.10.002

Simar, L., & Wilson, P. W. (2020). Hypothesis testing in nonparametric models of production using multiple sample splits. *Journal of Productivity Analysis, 53*, 287-303. https://doi.org/10.1007/s11123-020-00574-w

Su, W., Wang, Z., Zhang, C., & Balezentis, T. (2023). *Determinants of the innovation efficiency of strategic emerging enterprises: Evidence from the robust frontiers. In Economic Change and Restructuring (Issue 0123456789)*: Springer US. https://doi.org/10.1007/s10644-022-09480-7.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature, 49*(2), 326-365. https://doi.org/10.1257/jel.49.2.326

Teece, D. J. (2019). A capability theory of the firm: An economics and (strategic) management perspective. *New zealand Economic Papers, 53*(1), 1-43. https://doi.org/10.1080/00779954.2017.1371208

Theodore, K. (2009). Employment, growth and social stability in a developing economy. *Social and Economic Studies, 58*(3), 63-74.

Tsang, S.-S., Chen, Y.-F., Lu, Y.-H., & Chiu, C.-R. (2014). Assessing productivity in the presence of negative data and undesirable outputs. *The Service Industries Journal, 34*(2), 162-174. https://doi.org/10.1080/02642069.2013.763932

Wang, X., Han, L., & Yin, L. (2016). Environmental efficiency and its determinants for manufacturing in China. *Sustainability, 9*(1), 47. https://doi.org/10.3390/su9010047

Wilson, P. W. (2008). FEAR: A software package for frontier efficiency analysis with R. *Socio-Economic Planning Sciences, 42*(4), 247-254.