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Total Factor Productivity Growth in the Indian Textile Sector: A Panel Data Analysis of Technical Progress, Allocative Efficiency and Scale Effects

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ABSTRACT

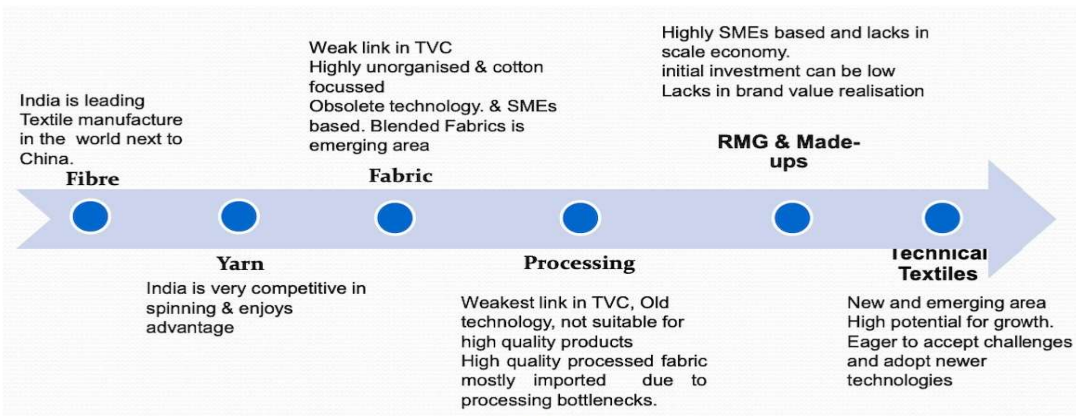
This study examines the Total Factor Productivity Growth (TFPG) and its key components—technical efficiency, technological progress, scale efficiency, and allocative efficiency—within the Indian textile sector, using firm-level panel data spanning from 1998 to 2018, sourced from the Annual Survey of Industries. The frontier production function is estimated through the Error Component Model (ECM), while the Divisia Tornqvist index is employed to decompose TFPG into its constituent components. Our findings reveal significant variability in productivity growth across the observed period, characterized by both positive and negative phases of growth. The fluctuations in TFPG indicate that firms in the Indian textile industry have faced considerable challenges in achieving consistent productivity improvements. These inconsistencies can be attributed to a range of factors, including market volatility, technological limitations, and inefficiencies in resource allocation. Additionally, our results suggest that while some firms have managed to achieve technical efficiency and scale economies, others have struggled, contributing to the overall variability in productivity growth. The study highlights the importance of targeted policy measures to foster technological innovation, improve resource utilization, and stabilize productivity growth within the sector. Strengthening these areas could enhance the competitiveness and sustainability of the textile industry in India.

KEYWORDS
Total Factor Productivity, Allocative Efficiency, Scale Efficiency, Technical Progress, Technical Efficiency, Error Component Model, Divisia-Tornqvist Index, Stochastic Frontier.

1. Introduction

The textile and apparel sector plays an important role in the economy of India. It is the second larges producer of Man-Made fiber. India is the third largest exporter of textile and apparel in world. The share of textile and apparel (T&A) including handicrafts in India's total merchandise exports stood at a significant 10.5% in 2021-22. India has a share of 4.6% of the global trade in textiles and apparel. Major textile and apparel export destinations for India are USA, EU-27 and UK, accounts for approximately 50% of India's textiles and apparel exports (Ministry of Textiles, 2023). The textiles and wearing apparel sector generated a gross value added (GVA) of INR 3.77 lakh crore (45.24 billion USD) in FY23, which was about 10.6% of the manufacturing GVA at current prices. The contribution of the Indian textile industry will almost double from the current 2.3% to 5% of GDP by 2030 (Fibre2Fashion, 2024). India's textile and apparel exports (including handicrafts) stood at USD 28.72 billion in FY24. The textile sector in India accounts for 2.3% contribution to the GDP on average, 13% contribution to the industrial production, and 12% contribution to the economies exports earnings (IBEF, 2023). The textile value chain in brief is presented below.

The present study is on the textile sector in India and it employs the Error Component Model (ECM) of Bat- tese and Coelli (1992), to estimate the stochastic frontier using panel data, from 1998 to 2018, incorporating a Translog production function with a time trend. This approach allows for the time-varying inefficiency effects to be modeled, capturing the dynamic nature of firm efficiency over the observed period. Additionally, the present study used the Divisia Tornqvist index to estimate Total Factor Productivity Growth (TFPG) and decompose it into its key components, including technical progress, changes in technical efficiency, scale efficiency, and allocative efficiency. This decomposition provides a detailed understanding of the various factors contributing to productivity changes across firms and over time.



The

Figure 1: Textile Industry Value Chain

Courtesy: Report on the Impact of Textile Industry on Income and Employment Generation by Textile Committee, Ministry of Textiles, Govt. of India

industry has experienced low productivity and declining worldwide market share, especially in the recent past, despite a number of innate qualities, favourable natural endowments, and numerous government programs. The epidemic caused the domestic market for India's textile and clothing industry to drop from 106 billion USD to 75 billion USD in 2020–21; however, it is expected to rise to 190 billion USD by 2026. Between 2015–16 and 2019–20, this sector's export share decreased by 6.7% as well. India's exports to the main markets—the United States, the United Arab Emirates, the United Kingdom, and the European Union—have decreased from 16,990 million USD in 2015–16 to 12,290 million USD in 2019–20. During the same time period, foreign direct investment (FDI) in this sector has decreased by about 48%. According to upstream supply chain connectivity, India's textile and apparel industry is a significant market for agri- cultural products, with many farmers supplying their goods to over 4000 ginning (the process of extracting cotton fibres from seeds) facilities and about 3500 textile mills. It is significant to highlight that, in spite of its importance in terms of employment

creation, especially for women, industrial
contribution, and foreign exchange earnings,
this sector lags behind many of India's Asian competitors in terms of technology. According to (Saheed, 2022), around 75% of the industrial looms in use in the nation are antiquated and out of date, lacking any process or quality control. In comparison to its rivals, like Singapore, China, South Korea, and Hong Kong, the textile sector in India accounts for a small portion of world exports, and it has not significantly improved during the post-liberalization era. Furthermore, from 28% in 1991 to 13% in 2015 (Dhiman, 2021), and to 14% in 2019 (Dhiman et al., 2020) prior to the pandemic, the proportion of Indian textile exports in the country's overall exports has also decreased. Nordås (2004) projected that China and India's proportion of global clothing exports will treble

following the Multi Fibre Agreement (MFA) phase- out in 2005. India's participation has increased from about 3% to 4% between 2000 and 2016, whilst China's portion has doubled from 18.2% to 36.7% during this time. Although India has a comparative advantage in this market, Vietnam and other developing economies like Bangladesh and Pakistan have emerged as major exporters of textile and clothing, especially after the MFA phase out in 2005 due to their low labour costs. As a result, they pose a threat to India's export competitiveness. The USA is the largest export market for the Indian textile and apparel industry (Kim, 2019). The percentage of clothing exported from India rose from 3% in 2000 to just 3.3% in 2018, compared to increases of 18% to 31.3% in China and 0.9% to 6.2% in Vietnam over the same period. Additionally, India's textile exports have seen only a slight increase in technology content compared to significant increases in China's and Vietnam's textile exports. During this time, Bangladesh and Vietnam have overtaken India in terms of their respective shares of global garment exports. For the Indian textile sector to remain competitive in the global market, technical modernisation is therefore necessary.
The total factor productivity in an important determinant of the future growth trajectory of an industry. It's role in the textile and apparel industries in India becomes all the more critical given the employment intensive nature of these sectors. The present paper seeks to explore and quantify the Total Factor Pro- ductivity Growth (TFPG) and decompose it into components of technological progress, technical efficiency, scale and allocative efficiency. The use of panel data obtained from Annual Survey of Industries (ASI), which is the most exhaustive firm level industrial survey in India, for the period of 1998 to 2018 and parametric technique of estimating the stochastic frontier using translog production function make this research stand apart from the existing literature on this topic.
The remainder of the paper is organized as follows. Next section presents a brief review of different theoretical and empirical literature reviewed on this issue. The is followed by the methodology which presents a brief overview of the statistical models used. This is followed by results and discussion sections as well as the conclusion and policy implications section.

2. Literature Review

The estimation and decomposition of Total Factor Productivity (TFP) have been widely studied across various industries, particularly in the context of understanding efficiency, technological progress, and input utilization. In the case of the Indian textile industry, the growing importance of productivity enhancement amidst competitive global markets and evolving technological frameworks has motivated extensive research. This study adopts the Divisia Tornqvist index to estimate TFP growth and decomposes it into its key com- ponents, such as technical efficiency, scale efficiency, and allocative efficiency, with a focus on the use of Error Component Models (ECM) in the estimation of the stochastic production frontier using a translog production technology and panel data on the Indian textile industry from 1998 to 2018. Previous literature provides a foundation for understanding the role of technological change, innovation, and resource allocation in shaping TFP trends, especially within industries that are labor-intensive and rely heavily on international trade, such as textiles. The following sections presents key studies that have examined TFP growth, its decomposition, and efficiency analysis using both parametric and non-parametric approaches, with a focus on the methodologies and findings most relevant to the Indian textile sector. Hulten (2001) offers an extensive review of the development of measurement approaches to total factor pro- ductivity and therefor is an essential paper to be reviewed in any work of the present kind. The paper traces the development of the concept from being a residual measure, to be computed using index numbers, to production function approach which was first proposed by Solow (1957). The paper also details several ar- guments by researchers that are critical to the Solow's proposal, including the Griliches and Jorgenson (1967) paper. The criticism to the production function approach stems mainly from the restrictive assumption that it imposes, such as, constant return to scale, perfect competition, and the assumption of technical change is Hicks neutral. The other problem with this production function approach to measuring productivity is that the measurement is based on the concept of Divisia index which is not necessarily path independent. Hulten (1973) explains the condition under which the index is path independent. This method has been briefly described in the methodology section of the present paper. Fare et al. (1994) was reviewed to understand theoretical concepts and practical applicaiton areas of Malmquist Productivity Index. The paper computes the productivity index and its decomposition into technical change and efficiency change, for 17 OECD countries from 1979 to 1988. Malmquist index is based on the idea of distance function. Distance functions represents multipe output and multiple inputs of firms as distance from the frontier. The ratio of these distances provide a measure of the productivity of firms. As opposed to the Tornqvist index of TFP, whic is a discrete form of Divisia index, this index is a quantity based index and does not require data on cost or revenue share.
Caves et al. (1982) explores the relationship between firms with different production technologies by defin- ing

and analyzing the input distance function, which carries the same informational content about a firm's technology as the traditional production function. The paper first derives the derivative of the distance function with respect to input and output variables by applying the implicit function theorem, connecting it directly to the production function. The Malmquist input index is then introduced as the ratio of the input distance functions between the firms. Assuming a translog distance function, the author demonstrates that for a firm minimizing costs, the derivative of the input distance function can be represented as the ratio of input prices. Building upon this foundation, the paper proves that the geometric average of the Malmquist indices of two firms (or the same firm over different time periods) equates to the Tornqvist input index. A parallel result is derived for the Tornqvist output index using the output distance function.

Further, the paper defines output- and input-based productivity measures and establishes their relationship with similar Tornqvist indices. It concludes by showing that the geometric mean of the Malmquist productivity indices of two firms equals the product of a scale factor and the Tornqvist index, a result that holds true for both input- and output-based measures.

There are various functional form, also called aggregator functions, to represent the input-output dynamics for a firm or industry. There are also various types of indexing approaches available for constructing ag- gregate price and quantity series for both input and output data. Cobb Dougla and CRS are examples of aggeagtor functions and Laspayers and Paasche indices and also the Fisher's Ideal index which is a product of the other two are exmples of indices for aggregating price and quantity data over multiple input and output. Diewert (1976) uses a theorem which says that under certain conditions, the aggregator function for period r denoted by $f(x^r) = (X^T A\, X)^{1/2}$ can be represented by Fisher's Ideal index. The conditions are, for an aggregator function $\max_x f(X): p^r \leq p^r X^r$ Where X^r is the solution and maximization takes place over a concave region of the feasible set. The theorem has been proved by econometricians like Frisch, Wald, Afriat and Pollak. It obviates the need of estimating the aggregator function, i.e. the coefficients in matrix A. If an aggregator function can be expressed as a quantity index, then it is said that the quantity index is exact for that aggregator. An index is called superlative if it is exact for an aggregator function which is a second order approximation of a linearly homogenous arbitrary function. Using quadratic approximation lemma that says $f(z^1) - f(z^0) = \frac{1}{2}[\nabla f(z^1) + \nabla f(z^0)](z^1 - z^0)$ where $\nabla f(z^r)$ is the gradient vector, the paper proves that Tornquvist is a superlative index for translog aggregator functions. This paper provides valuable insight to many important concepts related to index number theory.

Battese and Coelli (1992) presents the mechanics of Error Component Model (ECM) and its application on paddy production panel data for a village in India. The models propose several alternatives for the ineffi- ciency component of the composite error term. Besides the one specification discussed in the methodology section, paper proposes this $\eta_{it} = 1 + \eta_1(t - T) + \eta_2(t - T)^2$ two parameter specification. Additionally, the alternative specification proposed is $\gamma(t) = [1 + \exp(bt + ct^2)^{-1}]$ where $t = 1,2 \ldots etc$. The estimation model takes into account inputs such as irrigated and unirrigated land, bullock, labour, cost of inputs to build a model for the total value of output.

A comprehensive exposition of methodology and application of foundational concepts of Stochastic Frontier Analysis (SFA) has been provided in Kumbhakar and Lovell (2003). The book starts by introducing the basic concepts of efficiency, productivity, and the need for measuring them in various economic contexts. It distinguishes between technical efficiency (the ability to produce the maximum output from a given set of in- puts) and allocative efficiency (the ability to use inputs in optimal proportions given their prices). The book presents the theoretical foundations of SFA, emphasizing its stochastic nature, which accounts for random errors in production processes. He discusses the formulation of the stochastic frontier production function and the role of the error components—representing inefficiency and statistical noise. It also discusses ad- vanced topics in SFA, such as time-varying inefficiency, panel data applications, and the integration of SFA with other methodologies like data envelopment analysis (DEA). Kumbhakar highlights the flexibility of SFA in accommodating different assumptions about the distribution of inefficiencies.

Kathuria et al. (2011) conducts a comprehensive analysis of productivity measurement methodologies in the context of Indian manufacturing. It specifically compares various approaches, including Total Factor Productivity (TFP) measurement techniques, such as the Cobb-Douglas production function, stochastic frontier analysis (SFA), and data envelopment analysis (DEA). The authors aim to highlight the strengths and weaknesses of each method, as well as their implications for understanding productivity dynamics in the Indian manufacturing sector. The paper outlines different productivity measurement methods, detailing how each approach quantifies productivity and accounts for inputs and outputs. The authors emphasize the importance of selecting an appropriate methodology based on the specific characteristics of the industry being studied. Using data from Indian manufacturing firms, the authors apply the various methods to assess TFP growth over a specified period. They analyze how each approach handles issues such as input quality, returns to scale, and efficiency.

Goldar (2004) analyzes the productivity trends in Indian manufacturing before and after the economic re- forms initiated in the early 1990s. The study aims to assess the impact of these reforms on productivity growth, efficiency, and the overall competitiveness of the manufacturing sector. The paper begins by outlining the economic environment of India prior to the reforms, highlighting the challenges faced by the manufacturing sector, including protectionist policies, inefficiencies, and technological stagnation. The authors describe the major reforms implemented in the early 1990s, including liberalization, deregulation, and trade policy changes. These reforms aimed to enhance competition, encourage foreign investment, and promote techno- logical advancements. Employing various techniques of analysing the TFP, the paper reports a significant increase in productivity in the post-reform period compared to the pre-reform period. TFP growth rates improved markedly, suggesting that the reforms contributed to greater efficiency and competitiveness in the manufacturing sector.

Technical efficiency of a firm can be transient or long term. The Stochastic Frontier Model on cross sectional data does not capture the distinction between long term and transient inefficiencies. While firm level heterogeneities can be modelled using panel data as $\ln Y_{it} = (\omega_i - \eta_i) + f(\ln X_{it}; \beta) + (V_{it} - U_{it})$ where ω_i captures the unobserved heterogenieties, η_i represents the persistent inefficiencies and U_{it} is the transient inefficiency component. The parameters of the model are estimated using simulated log likelihood function. The paper further explores the beta convergence, also called the catching up effects. The paper concludes that there exist catching up by inefficient firms despite the existence of both transient and persistent inefficiencies.

Joshi and Singh (2012) examined the technical efficiency of the Indian garment industry using cross-sectional data from 275 firms across various states for the year 2004–2005. They employed a two-stage analytical pro- cess: first, Data Envelopment Analysis (DEA) was used to measure technical efficiency scores, and then Tobit regression was applied to identify factors affecting efficiency. The findings revealed that garment firms could potentially increase output by 32.1% by improving input-use efficiency and optimizing plant size. Overall technical efficiency was found to be more sensitive to variations in pure technical efficiency than scale efficiency. The study also indicated that micro-sized firms were more efficient in resource utilization than small and medium-sized firms. Factors such as labor productivity, wages per employee, and labor-staff ratio positively influenced efficiency, while investment in plant and machinery and outstanding loans had a negative impact.

An application of the Error Component Model and the Technical Efficiency Effect (TEE) model can be seen in Rodr´ıguez and Elasraag (2015). In the TEE model, the inefficiency term U_{it} is assumed to have $N^+(m_{it}, \sigma^2)$ distribution. Where $m_{it} = z_{it}\delta$ with z_{it} being the vector of variables that may have an effect on the technical efficieny of the firm and δ being a vector of parameters to be estimated. The paper assesses and decomposes the TFP in Egyptian cotton production using both the approaches. Based on the available data and estimations, this research makes a distinct contribution to the existing literature by providing a comprehensive and detailed estimation and decomposition of Total Factor Produc- tivity (TFP) in the Indian textile industry using panel data over an extended time period. While previous studies have predominantly focused on TFP estimation using aggregate data or cross-sectional approaches, this research employs a more advanced methodological framework by combining the Divisia Tornqvist index for TFP decomposition with the Error Component Model (ECM) for estimating the stochastic frontier. This allows for the dynamic analysis of firm-level efficiency over time, capturing both technical inefficiencies and the role of time-varying factors such as technological progress. Moreover, this study addresses the specific gaps in the literature regarding the interplay between allocative efficiency, scale efficiency, and technical efficiency within the Indian textile sector—areas that have been relatively under explored in previous research. By focusing on firm-level data, this research provides granular insights into how productivity drivers differ across firms and over time, highlighting the impact of technological adoption, policy reforms, and structural shifts in the sector. Ultimately, this study fills the research gap in the dynamic decomposition of TFP within an industry that is crucial to India’s economic growth and international competitiveness, providing a more nuanced understanding of the factors affecting productivity growth at the micro level.

3. Data

Year by year raw date of the Annual Survey of Industries (ASI) was released in block (A to J) by the Data Informatics and Innovation Division (DIID) of the Ministry of Statistics and Programme Implementation (MoSPI), Government of India. The factory identifiers and all five-digit codes are contained in Block A of the raw data, whereas the other blocks contain information on the factor input and output variables. The factory identifier was mapped to every block in Excel using the vlookup tool. Ultimately, a single sheet with all the pertinent block data was assembled. By eliminating manufacturers with insufficient year-by-year data, the final panel data was acquired. KNN imputation with K = 4 was used when needed to fill in the missing data. With 209–214 textile companies and 87–91 apparel companies, the panel that was created as a result is quite uneven. The examination of the textile industry is carried out with data from 1998 to 2018, while the analysis of the clothing industry is restricted to data from 2007 to 2018 because of data accessibility issues. The research made use of output, capital, labour, energy, and material data, and it followed a standard procedure for data editing for the apparel and textile industries. The factor inputs and output have the following measurement values. The ex-factory value of output determines how output is measured. The total purchase price of electricity generated on-site, electricity purchased, fuels such as coal, diesel and petrol, and other fuels consumed is used to calculate energy. Salary and bonuses, as well as welfare costs for employees hired directly or under contract, are used to quantify the labour factor input. The closing value of working capital indicates the total domestic input, which comprises inventories of raw materials,

Table 1: Summary Statistics (in Rupees lakhs)

Statistic	Capital	Labor	Material	Energy	Output
Min	0.48	14.96	0.17	4.25	8.47
1st Qu.	379.7	297.7	552.3	354.7	2912.0
Median	1163.0	621.8	1524.0	716.2	6339.0
Mean	4461.0	1191.0	3983.0	1307.0	13970.0
3rd Qu.	3759.0	1476.0	3629.0	1426.0	13440.0
Max	599100.0	20750.0	83710.0	47690.0	231000.0

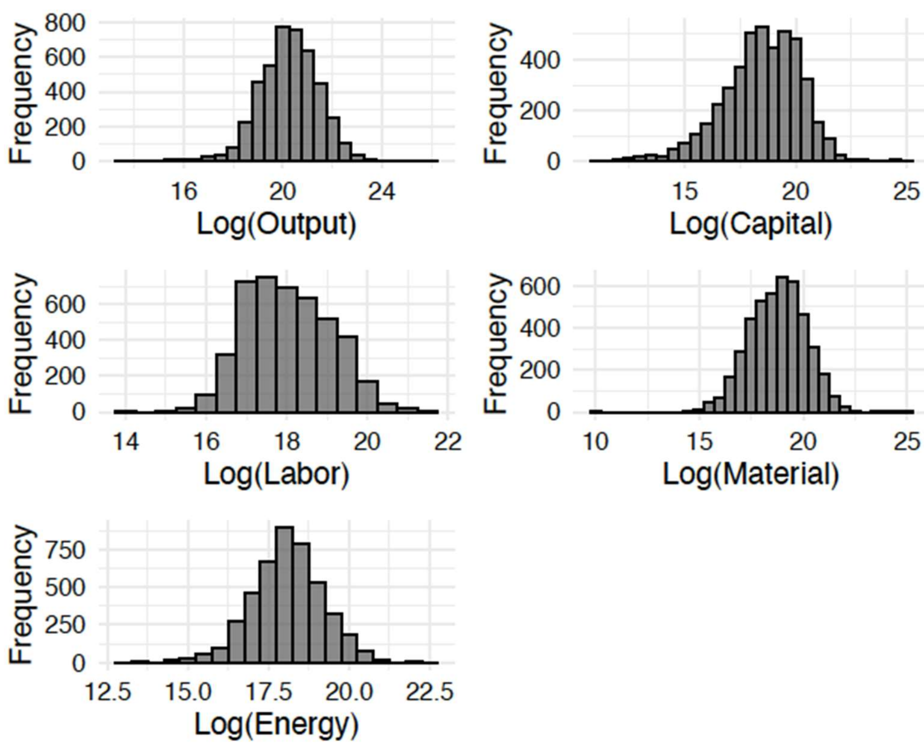


Figure 3: Distribution of Output and Factor Inputs

spares, work-in-progress, and finished goods. This total is used to calculate the material input. The purchase value at delivery serves as the benchmark for imported material. Conversely, capital assets comprise plant, machinery, computers, and transportation machinery and are valued at closing, net of depreciation. With a variety of deflators,

the data was inflated from nominal to real values. These deflators included the consumer price index-industrial workers (CPI-IW), for labour wages; the wholesale price index (WPI) for manufacturing of textile and apparel group; output; the WPI for manufacturing of machinery for textile apparel and leather products; capital assets; the WPI for fuel and power; the energy consumption; the WPI for non-food articles (fibre group); and the WPI for material. 2011–2012 served as the base year for the deflation of
all data used in the research of the textile and apparel industries, with the exception of labour salaries. Using 2016 as the base year, labour pay values are deflated. The investigation is carried out over a period of time that includes several WPI and CPI pricing series in addition to multiple NIC classification schemes. One pricing series was linked to another using the appropriate linking factors, and care was taken to make sure the correct NIC codes were used when mapping the firms.

The scatter plot of energy uses versus output, with both variables represented on a logarithmic scale, reveals a positive relationship between the two. As energy use increases, output tends to rise as well, indicating that higher energy consumption is generally associated with greater production levels. However, the scatter of points also suggests that this relationship is not perfectly linear, and the degree to which energy contributes to output appears to vary among firms.

The positive association implies that energy is an important input in the production process. Firms that consume more energy tend to have higher output, potentially reflecting the energy-intensive nature of the sector. However, the dispersion of the points also indicates that factors other than energy, such as technology, labor, or capital efficiency, likely play significant roles in determining output. While energy is a key driver of output, the variability in the relationship suggests that firms may benefit from optimizing energy use in conjunction with other inputs to maximize their productivity. Further analysis could investigate the efficiency of energy use across firms, as well as how technological factors or scale efficiencies contribute to the differences observed in the energy-output relationship.

The below table presents a summary statistics of all input variables and output.

The presence of outliers in all input and output variables is clear from the descriptive statistics as well as the histograms. These outliers were removed before performing regression. 1.5 times the interquartile range below the quartile one data point was taken as the lower bound while 1.5 times the interquartile range above the quartile three data point was taken as the upper bound.

4. **Methodology**

The input output relationship for firms can be modelled by the production function. $\boldsymbol{Q_{it}} = \boldsymbol{f(X_{it}, t;\ \beta)}$, where $\boldsymbol{f(X_{it}, t;\ \beta)}$ is the deterministic kernal of the production function which represents the production frontier, that is, the maximum achievable output from the given input under the given technology. This function can take several forms such unit elasticity of substitution, constant elasticity of substitution, translog production function etc. $\boldsymbol{Q_{it}}$ represents the output of firm $\boldsymbol{i}$ at time $\boldsymbol{t}$ and $\boldsymbol{X_{it}}$ represents the input vector for firm $\boldsymbol{i}$ at time $\boldsymbol{t}$, $\boldsymbol{\beta}$ is the vector of parameters to be estimated and $\boldsymbol{t}$ is the variable representing time. This is an example of a deterministic frontier. In reality, the actual output of firms may differ from the one estimated by the frontier due to a) the idiosyncratic error, also known as random fluctuations or random noise in the data and b) the presence of technical inefficiency in the firms. The two phenomenon can be included in the model as

$$\boldsymbol{Q_{it} = f(X_{it}, t; \beta) e^{v_{it}} e^{-u_{it}}} \qquad (1)$$

Where $\boldsymbol{v_{it}}$ is the idiosyncratic error term and $-\boldsymbol{u_{it}}$, with $\boldsymbol{u_{it} \geq 0}$, is the inefficiency term for the firm $\boldsymbol{i}$ at time $\boldsymbol{t}$. The negative sign on the inefficiency terms indicates that its effect is to pull the firm down from the frontier. Inclusion of these terms in the exponential form helps in log linearisation of the model as

$$Ln(Q_{it}) = Ln\ (f(X_{it}, t; \beta)) + \epsilon_{it}$$

where $\epsilon_{it} = v_{it} - u_{it}$ is called the composite error term. The estimation of β parameters and firm specific inefficiencies require making distributional assumptions on the idiosyncratic error term and the inefficiency term. Although there are many options for distributional assumption on the two terms, the most commonly used for empirical analysis are, $v_{it} \overset{iid}{\sim} N(0, \sigma_v)$ and $u_{it} \overset{iid}{\sim} N^+(\mu, \sigma_u)$ that is, the idiosyncratic error has a normal distribution and the inefficiency term has a half normal distribution (normal distribution truncated above at the mean). With this model, the technical efficiency of a firm can be estimated as

$$e^{-u_{it}} = \frac{Q_{it}}{f(X_{it}, t;\ \beta)}$$

for the firm i at time t.

The model proposed by Battese and Coelli (1992), also known as the Error Component Model (ECM) is the most widely used model for estimation of total factor productivity and its components. This paper used ECM for the estimation of the stochastic frontier. The essential features of the model are presented here for a ready reference to the reader. In the ECM model, the error term, $\boldsymbol{u_{it}}$ is defined as $\boldsymbol{u_{it} = u_i \exp[-\eta\ (t - T)]}$, where the distribution of $\boldsymbol{u_i}$ is taken to be $\boldsymbol{u_i \overset{iid}{\sim} N^+(\mu, \sigma_u^2)}$ that is, it has a firm specific part $\boldsymbol{u}$ with the half normal distribution (truncation at zero of the normal distribution with mean $\boldsymbol{\mu}$ and variance $\boldsymbol{\sigma_u^2}$) and a time specific part $\boldsymbol{\exp\ [-\eta(t - T)]}$. Here $\boldsymbol{\eta}$ is a parameter representing proportional rate of change in technical efficiency. if $\boldsymbol{\eta}$ is positive then there is improvement in technical efficiency overtime while a negative $\boldsymbol{\eta}$ represents deteriorating technical efficiency trend. This can be easliy seen if one considers how $\boldsymbol{Q_{it}}$, the output will be impacted with positive and negative sing of $\boldsymbol{\eta}$.

The derivative of the deterministic frontier, $\boldsymbol{f\ (X_{it}, t;\ \beta)}$, with respect to time is called the technological progress (TP) and it graphically represents shift in the frontier with time.

$$\frac{d \ln f(X_{it},t;\beta)}{dt} = \frac{\partial \ln f(X_{it},t;\beta)}{\partial t} + \frac{\partial \ln f(X_{it},t;\beta)}{\partial \ln X}\frac{d\ ln\ X}{dX}\frac{dX}{dt}$$

Here the term, $\frac{\partial \ln f(X_{it},t;\beta)}{\partial \ln X}$ is the elasticity of the $\boldsymbol{i^{th}}$ input and the term $\frac{d\ ln\ X}{dX}\frac{dX}{dt}$, being the derivative of the natural log of a variable, is it proportionate rate of change. Hence,

$$\frac{d \ln f(X_{it},t;\beta)}{dt} = TP + \textstyle\sum_i E_i\, \dot{x}_i \qquad (2)$$

Where $\boldsymbol{E_i}$ represents the elasticity of the $\boldsymbol{i^{th}}$ input. The summation is due to there being more than input and the chain rule of differentiation. Also the time derivative of output in log form represents its proportionate rate of change and, by combining equation (1) and (2), can be represented as,

$$\dot{Q}_{it} = TP + \textstyle\sum_i E_i\, \dot{x}_i - \frac{du_{it}}{dt} \qquad (3)$$

The dot above $\boldsymbol{Q_{it}}$ represents the proportionate rate of change in the outut. The derivative of the ran- dom noise with respect to time is zero because of it random nature. This represents the decomposition of the change in output into components of technical progress, weighted sum of change in input with elasticities being the weight and change in technical efficiency which is represented by $\frac{du_{it}}{dt}$, for each firm in each year.

The total factor productivity is defined as the portion of output growth that cannot be explained by growth in factor input. Total Factor Productivity (TFP) is a measure of the efficiency with which a firm or an economy transforms multiple inputs—such as labor, capital, energy, and materials—into output. It captures the portion of output growth that cannot be explained by the growth in input usage. Instead, TFP reflects improvements in the production process, such as advancements in technology, better management practices in terms of allocation of inputs, innovation, and improvements in worker skills, scale efficiency among other factors.

In the present context, the Total Factor Productivity Growth (TFPG) can be expressed as,

$$T\dot{F}P = \dot{Q} - \textstyle\sum_i C_i\, \dot{X}_i \qquad (4)$$

This is the discrete time approximation of the Divisia Index and is know as Tornquvist Index of Total Factor Productivity.

Substituting equation (1) in equation (2) gives,

$$T\dot{F}P = TP + \textstyle\sum_i E_i \dot{X}_i - \sum_i C_i \dot{X}_i - \frac{du_{it}}{dt} \qquad (5)$$

This equation implies that TFPG is a residual and provides a non-parametric way of measuring it. This non-parametric measure does not assume any functional form for the production technology. It also does not make any assumption related to the return to scale. Equation (3) can be rewritten as,

$$TFPG = TP - \frac{du_{it}}{dt} + (RTS - 1)\textstyle\sum_j \epsilon_j\, \dot{X}_j + \sum_j(\epsilon_j - C_j)\, \dot{X}_j \qquad (6)$$

where, $\boldsymbol{TFPG}$ is the rate of Total Factor Productivity Growth, $\boldsymbol{TP}$ is Technical Progress, $\frac{du_{it}}{dt}$ represents the change in technical inefficiency over time, $\boldsymbol{RTS}$ is Returns to Scale which equals the sum of elasticities of all the factor inputs, $\boldsymbol{\epsilon_j}$ is the elasticity share of the $\boldsymbol{j^{th}}$ input, $\boldsymbol{C_j}$ is the cost share of the $\boldsymbol{j^{th}}$ input, $\dot{\boldsymbol{X}}_j$ is the growth rate of the $\boldsymbol{j^{th}}$ input. Equation (6) decomposes TFPG into different components.

The translog production technology used in the present study is as follows.

$$\begin{aligned}
&\boldsymbol{Ln(output_{it}) = \beta_0 + \beta_K Ln(capital_{it}) + \beta_L Ln(labour_{it}) + \beta_M Ln(material_{it}) +} \\
&\boldsymbol{\beta_E Ln(energy_{it}) + \tfrac{1}{2}\beta_{KK}\,\mathrm{Ln}(\mathrm{capital}_{it}^2) + \tfrac{1}{2}\beta_{LL} Ln(labour_{it}^2) + \tfrac{1}{2}\beta_{MM} Ln(material_{it}^2) +} \\
&\boldsymbol{\tfrac{1}{2}\beta_{EE} Ln(energy_{it}^2) + \beta_{KL} Ln(capital_{it}) Ln(labour_{it}) + \beta_{KM} Ln(capital_{it})\, Ln(material_{it}) +} \\
&\boldsymbol{\beta_{KE} Ln(capital_{it}) Ln(energy_{it}) + \beta_{LM} Ln(labour_{it})\,\mathrm{Ln}(material_{it}) +} \\
&\boldsymbol{\beta_{LE}\, Ln(labour_{it}) Ln(energy_{it}) + \beta_{ME} Ln(material_{it}) Ln(energy_{it}) + \beta_t t + \tfrac{1}{2}\beta_{tt} t^2 +} \\
&\boldsymbol{\beta_{Kt} Ln(capital_{it}) t + \beta_{Lt} Ln(labour_{it}) t + \beta_{Mt} Ln(material_{it}) t + \beta_{Et} Ln(energy_{it}) t}
\end{aligned} \tag{7}$$

Results and Discussions

Below is the table 2 of stochastic frontier regression output. The regression summary from the stochastic frontier analysis model provides several key insights into the production process and efficiency dynamics. Firstly, it is observed that the energy input has a highly significant and positive coefficient, indicating that energy plays a crucial role in enhancing output. However, the interaction between material and energy inputs is negative and significant, suggesting a complex relationship where increasing energy use may reduce the marginal productivity of materials.

The negative coefficients for all interaction terms involving energy in the stochastic frontier regression, except for the squared term of energy, suggest that there is a diminishing marginal effect of energy when combined with other inputs like labor, capital, and materials. This implies that as energy is used in conjunction with these other inputs, the overall productivity gains from energy decreases. In economic terms, this could indicate that energy is acting as a substitute rather than a complement to these inputs, reducing their marginal productivity. This could happen in situations where excessive energy use might not be effectively enhancing production due to inefficiencies or where an optimal balance between energy and other inputs has not been achieved.

Additionally, significant positive interaction terms, such as those between labor and materials and between capital and materials, indicate complementarity between these inputs.

Interestingly, the coefficients for the time trend and its square are both negative and significant. This suggests that while there has been technical progress over time, this progress may be slowing down. This deceleration in technical progress could be due to technological saturation or a reduction in innovation within the sector. The model also sheds light on the returns to scale for different inputs. Positive coefficients for squared terms like the energy term suggest increasing returns to the energy input, while negative coefficients such as for material indicate diminishing returns to material input.

The analysis further reveals complementarity and substitution effects among the inputs. Positive interaction terms between labor and materials and between capital and materials suggest that these inputs are complements, where an increase in one input enhances the productivity of the other. Conversely, negative interaction terms, such as those between labor and energy and between material and energy, imply substitution effects or diminishing marginal returns when these inputs are used together.

The coefficient gamma, which is highly significant, indicates that a large portion of the total variance in output is due to inefficiency rather than random noise. This finding suggests that there is considerable room for improvement in the technical efficiency of firms. The log-likelihood value of -1617.013 provides a measure of model fit, and while this value alone does not indicate goodness-of-fit, it can be useful for comparing this model to others, such as the Cobb-Douglas specification.

The estimated value of $\boldsymbol{\eta}$ is -0.0047, indicating a slight but consistent decline in technical efficiency over time for the firms in the sample.

The analysis is conducted on a panel data set with 213 cross-sections (firms) over 21 time periods, indicating a robust longitudinal dataset. However, the data on 35 firms are missing in the original dataset, which should be considered when interpreting the results.

These findings have several implications. The significant impact of energy on output suggests that energy efficiency measures could enhance productivity. However, the negative interaction with materials indicates that careful management is required to optimize the use of these inputs together. The slowing technical progress suggested by the negative time coefficients may imply a need for innovation

Table 2: Summary of Stochastic Frontier Analysis Model

Variable	Estimate	Std. Error	z-value	Pr(> |z|)
Intercept	8.2274	2.1813	3.772	0.00016 ***
log(labor)	-0.1510	0.2787	-0.542	0.58795
log(capital)	-0.1071	0.1040	-1.030	0.30313
log(material)	-0.3279	0.1457	-2.251	0.02438 *
log(energy)	1.0268	0.2311	4.444	8.84×10^{-6} ***
log(labor)^2	0.0256	0.0222	1.152	0.24948
log(capital)^2	0.0064	0.0050	1.294	0.19561
log(material)^2	-0.0305	0.0117	-2.602	0.00928 **
log(energy)^2	0.0825	0.0202	4.076	4.58×10^{-5} ***
log(labor) · log(capital)	-0.0322	0.0149	-2.166	0.03029 *
log(labor) · log(material)	0.1335	0.0231	5.779	7.51×10^{-9} ***
log(labor) · log(energy)	-0.1168	0.0323	-3.613	0.00030 ***
log(capital) · log(material)	0.0863	0.0122	7.081	1.43×10^{-12} ***
log(capital) · log(energy)	-0.0401	0.0161	-2.486	0.01293 *
log(material) · log(energy)	-0.0895	0.0250	-3.583	0.00034 ***
time	-0.0659	0.0218	-3.018	0.00254 **
time^2	-0.0018	0.0003	-5.488	4.06×10^{-8} ***
time · log(labor)	0.0018	0.0014	1.294	0.19561
time · log(capital)	-0.0092	0.0009	-10.307	$< 2.2 \times 10^{-16}$ ***
time · log(material)	-0.0021	0.0012	-1.793	0.07295 .
time · log(energy)	0.0151	0.0017	8.694	$< 2.2 \times 10^{-16}$ ***
sigmaSq	0.5408	0.0667	8.110	5.08×10^{-16} ***
gamma	0.8066	0.0248	32.533	$< 2.2 \times 10^{-16}$ ***
η	-.0047	.0031	-1.4782	.1393
Model Statistics				
Log-Likelihood	-1617.013			

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 Panel Data Information:*
Number of cross-sections = 213 Number of time periods = 21
Total number of observations = 4438 (35 observations not included in the panel)

policies or investments in new technologies within the industry.

This regression analysis offers valuable insights into the production structure and efficiency dynamics of the firms. It highlights the importance of managing input interactions, especially between energy and materials, and suggests that there may be opportunities to enhance technical efficiency. Further exploration of technical progress and efficiency changes over time could provide a deeper understanding of productivity dynamics in this sector. The analysis of Total Factor Productivity Growth (TFPG), its components—allocative efficiency, scale efficiency and the firm-wise distribution of technical progress provides a comprehensive picture of the dynamics affecting productivity in the sector (Table 3). Each of these factors plays a critical role in determining overall firm performance, and the implications of their behavior over time reveal both the challenges and opportunities present within the industry.

The periods of negative TFPG are particularly concerning, as they indicate that some firms are failing to maintain productivity levels, which could have long-term consequences for competitiveness in the sector. The general variability points to an underlying structural issue where firms may not be fully exploiting their resources or responding adequately to changing market dynamics. The allocative efficiency component, which measures how well firms allocate their inputs to maximize output, shows a more stable yet slightly negative trend. This consistent underperformance in allocative efficiency suggests that many firms are not optimizing their input use. This could be due to a variety of factors, such as mismanagement of resources, failure to adapt to changing input prices, or rigidities in production processes. A persistently negative allocative efficiency trend implies that even though firms may be investing in inputs, they are not doing so in a way that maximizes output, thereby undermining potential productivity gains. This inefficiency is a key area of concern and suggests that improving resource allocation strategies could yield significant improvements in productivity growth. Scale efficiency, which reflects the gains or losses from changes in the scale of production, also fluctuates over time but generally exhibits positive values. This indicates that, on average, firms are benefiting from increasing returns to scale, meaning that expanding production leads to higher productivity. However, the fluctuations in scale efficiency suggest that these gains are not consistent across all firms or over time. Some firms may be expanding too rapidly or too slowly relative to their optimal scale, while others may not be able to exploit economies of scale due to structural or operational limitations. The positive but variable scale efficiency indicates that while many firms are benefiting from increased scale, there is still room for improvement in how firms manage production expansion. When integrating the implications of TFPG, allocative efficiency, scale efficiency, and technical progress, a clear picture emerges of a sector that is experiencing uneven growth and faces significant challenges in realizing its full productivity potential. The fluctuating and often negative TFPG is a reflection of inefficiencies in both resource allocation and the adoption of new technologies. Despite some firms benefiting from economies of scale, the overall sector appears to struggle with consistent productivity improvements. The persistent underperformance in allocative efficiency suggests that firms are not making the most of the resources they have, whether due to misallocation, mismanagement, or external constraints. This inefficiency, combined with the slow rate of technical progress for most firms, creates a situation where firms are not able to leverage technological advancements to improve their productivity. The histogram of technical progress further reinforces this point, as only a few firms are making meaningful strides in improving their technology, while many are either stagnant or regressing. For firms in the sector to improve their productivity, efforts need to be focused on several key areas. First, firms must improve how they allocate resources to maximize output, which may require better management practices, investment in training, or more flexible production processes. Second, firms need to actively pursue technological advancements, whether through internal innovation or the adoption of external technologies. This will be crucial in driving long-term productivity growth and ensuring that firms remain competitive in an increasingly globalized market. Lastly, firms should carefully manage their scale of production, ensuring that they can reap the benefits of increasing returns to scale without overextending their resources or facing diminishing returns. In conclusion, the analysis suggests that the sector is characterized by uneven growth, with some firms benefiting from scale efficiencies and technological advancements, while others lag behind due to poor resource allocation and stagnating technical progress. For the sector to achieve sustained and broad-based productivity growth, significant improvements in allocative efficiency and technological innovation will be essential. Addressing these inefficiencies will enable firms to fully capitalize on their scale advantages and drive more consistent TFPG over time.

Year	Technical Progress	Allocative Efficiency	Scale Efficiency	TFPG	Technical Efficiency
1998	0.0247	NA	NA	0.0247	0.8040
1999	0.0237	-0.0581	0.0578	0.0120	0.7926
2000	0.0233	-0.2284	0.1671	-0.0500	0.7802
2001	0.0216	-0.0928	0.0507	-0.0329	0.7671
2002	0.0204	0.0654	0.1363	0.2090	0.7539
2003	0.0187	0.0106	0.0684	0.0841	0.7414
2004	0.0176	-0.0576	0.0628	0.0086	0.7276
2005	0.0153	0.0005	0.1396	0.1407	0.7131
2006	0.0121	-0.0164	0.0905	0.0709	0.6978
2007	0.0105	-0.1375	0.0931	-0.0498	0.6813
2008	0.0072	-0.4239	0.0388	-0.3950	0.6641
2009	0.0066	-0.0654	0.3631	0.2871	0.6465
2010	0.0061	-0.4105	0.2106	-0.2115	0.6255
2011	0.0044	-0.6888	0.6009	-0.1015	0.6102
2012	0.0064	-0.5535	0.2065	-0.3595	0.5933
2013	0.0044	-0.1794	0.1995	0.0051	0.5743
2014	0.0040	-0.5668	0.0869	-0.4952	0.5559
2015	0.0017	-1.1062	0.3125	-0.8117	0.5351
2016	-0.0016	0.0588	0.1003	0.1373	0.5139
2017	-0.0026	-0.1703	0.0769	-0.1166	0.4947
2018	-0.0045	-0.0296	0.0436	-0.0110	0.4764

5. Conclusion and Policy Implications

The results reveal significant variability in TFPG, with periods of both positive and negative growth. This inconsistency suggests that firms within the sector have faced challenges in maintaining stable productivity growth, potentially due to market fluctuations, technological limitations, or inefficiencies in resource utilization. The overall fluctuating trend in TFPG indicates that firms have struggled to continuously improve their output per unit of resources deployed, which is crucial for long-term productivity gains and competitiveness in both domestic and inter- national markets. Technical progress, while generally positive, has been minimal over the years, with some periods even showing negative values. This slow rate of technological advancement indicates that many firms are not adopting new technologies at the pace required to remain competitive. Firms that do manage to adopt new technologies tend to experience more significant productivity gains, but these firms are the exception rather than the rule. The small improvements in technical progress suggest that the sector may be falling behind in terms of innovation and technological upgrades, which could negatively impact the sector's export competitiveness. As global competition increases, the sector must accelerate its technological progress to keep up with com- petitors who are investing in more advanced production techniques and technologies. Technical efficiency, another critical component, has shown a declining trend, indicating that firms are be- coming less capable of maximizing output with the given resources. This decline in technical efficiency means that more resources are being wasted or underutilized, which directly reduces productivity. For a sector like textiles, where margins are often thin, technical inefficiency can severely impact profitability and output per unit of resources deployed. This inefficiency not only hampers the firms' ability to compete in export markets but also limits their ability to create new jobs, as more resources are being spent to achieve the same or even lower output levels. Allocative efficiency has also remained low and somewhat negative in certain periods, reflecting the sector's difficulty in optimally allocating resources such as labor, capital, and energy. This misallocation of resources implies that firms are not making the best possible use of their inputs, further reducing productivity. Poor allocative efficiency leads to higher costs per unit of output, weakening firms' competitive edge in global markets where cost efficiency is key. This inefficiency also affects employment generation negatively, as firms struggle to grow and expand due to their inability to fully optimize input allocation. On the other hand, scale efficiency has fluctuated over time but has generally remained positive, indicating that many firms have managed to benefit from economies of scale to some extent. Firms that are able to scale up production efficiently tend to experience cost savings and productivity gains, which are critical for boosting output per unit of resources deployed. However, the variability in scale efficiency across firms suggests that not all firms are operating at their optimal production scale, which further contributes to the inconsistent growth in Total Factor Productivity. For firms that are able to achieve greater scale efficiency, the potential for increasing output without proportional increases in input could lead to better export performance and higher employment opportunities. Still, the uneven distribution of these benefits across the sector highlights the need for targeted policies to help smaller firms grow and optimize their scale. To address the challenges identified in the analysis of TFPG and its components, several policy measures need to be considered. First, there is a clear need to accelerate technological adoption in the textile sector. Government incentives for research and development, along with subsidies or tax breaks for firms that invest in advanced production technologies, can help drive technical progress. Additionally, providing platforms for knowledge sharing and technology transfer between firms, particularly between large, technologically advanced firms and smaller enterprises, can help disseminate best practices and innovations more widely across the sector. Second, the decline in technical efficiency suggests that firms may benefit from programs aimed at improving operational efficiency. This could include government-sponsored training programs focused on process optimization, lean manufacturing, and resource management. Encouraging firms to adopt modern management practices and providing them with the tools and knowledge to do so would be key in reversing the trend of declining technical efficiency. Such improvements in operational efficiency could lead to higher output per unit of input and create a more competitive export base for the textile sector. Allocative efficiency can be improved by implementing policies that promote more flexible and responsive resource allocation. This could involve reforms in labor and capital markets to reduce rigidities that prevent firms from reallocating resources efficiently. Additionally, introducing financial products or credit facilities tailored to the needs of the textile sector could help firms invest in the right mix of inputs, such as new machinery, skilled labor, or energy-saving technologies, which would ultimately improve allocative efficiency. In terms of scale efficiency, policies that promote the growth and expansion of smaller firms, such as access to affordable financing, business development services, and market access programs, could help firms achieve the scale necessary to optimize production costs. By helping smaller firms grow, the sector could benefit from the increased productivity that comes with scaling production, which would improve competitiveness in both domestic and international markets. Moreover, the resulting increase in production capacity could lead to more employment opportunities within the sector. Finally, a focus on enhancing export competitiveness is crucial. The findings suggest that inconsistent productivity growth is limiting the sector's ability to compete internationally. By improving overall productivity through better technology, resource allocation, and scaling, the textile sector could better position itself in global markets. Policymakers could focus on reducing trade barriers, negotiating better trade agreements, and supporting export marketing initiatives to help firms penetrate new markets and sustain long-term growth. In conclusion, the findings from the TFPG analysis reveal critical weaknesses in the textile sector's productivity dynamics, driven by inefficiencies in technical progress, allocative efficiency, and technical efficiency. Addressing these inefficiencies through targeted policies will be crucial in improving output per unit of resources deployed, strengthening export competitiveness, and generating employment in the sector. By focusing on technology adoption, improving operational and allocative efficiency, and helping firms optimize their scale of production, the sector can achieve more consistent and sustainable productivity growth.

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