Scale Economies and Input Contributions: Evidence from Log-Linear and Translog Production Functions

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Abstract

This study analyzes the determinants of gross output (GO) using the Cobb–Douglas and Translog production functions for the years 2005 to 2025. The relationship between labor (L) and capital (K) inputs and production performance is examined using a time-series econometric approach. Secondary data were collected from various reports of the MoSPI, RBI, and NITI Aayog. The Cobb–Douglas production function was used to estimate output elasticities and returns to scale, and the Translog production function was used to account for non-linearities and substitution effects between inputs. The findings reveal that capital has a greater contribution to gross output than labor ,which reflects the capital intensity of the industry. The estimated returns to scale suggest increasing returns to scale in the production. The marginal productivity of the production factors exhibited a decreasing trend in the Translog model, while there were positive interaction effects between labor and capital, reinforcing complementarities between production factors. Even though there were temporary disruptions during the COVID-19 period, there are indications of increased productivity over time from the trends in technical and allocative efficiency. Overall, the study indicates that technological progress, resource allocation efficiency, and capital accumulation are important factors for improving production efficiency and productivity growth. Comparative specification (Cobb-Douglas vs. Translog) provides a wider picture of the structure of production and economies of scale in the industry. Panel data by region or industry could also be incorporated in future studies to provide a better understanding of the spatial variation in production behaviors. Other factors, such as technology adoption, infrastructure, and human capital, can further reinforce the analysis. Further insights may be gained through advanced econometric methods, such as structural equation modelling, ARDL models, and stochastic frontier analysis, as well as an analysis of long-run productivity dynamics and structural changes after the pandemic.

Keywords: Cobb–Douglas Production Function, Translog Production Function, Gross Output, Output Elasticity, Returns to Scale, Total Factor Productivity, Technical Efficiency, Capital Intensity, Input Substitution, Technological Progress, Econometric Modelling, Production Economics

Introduction

A key focus of production economics is the link between inputs and outputs. Gross output (GO) is an important measure of economic activity that captures the joint effects of labor and capital inputs in production. The Cobb-Douglas production function is commonly used in conventional production analysis because of its simplicity and interpretability. However, its assumptions of constant elasticity of substitution and returns to scale restrict its use in modelling complex production processes.

This study also includes the Translog production function, a flexible functional form that can capture variable elasticities and cross-elasticities. This integrated approach offers a better understanding of the production trends.

The study uses time series data from 2005-2025 to, and considers aggregate production rather than a regional breakdown. This approach allows the analysis of long-term dynamics, structural changes, and relative input contributions to the production process. This research is timely, given the changing economic environment, including technological advancements and external shocks (such as COVID-19), which affect production structures.

Objectives of the Study

1. To estimate the level of gross output, labour and capital inputs using the Cobb-Douglas production function.
2. To examine production using the flexible Translog production function.
3. To calculate input elasticities and analyse the returns to scale.
4. To examine the fit and explanatory ability of the Cobb-Douglas and Translog models.
5. To examine the impacts of labour and capital on gross output over time.

Significance of the Study

This study is significant both theoretically and empirically. It compares the Cobb-Douglas and Translog production functions, providing further insights into the methodological aspects of production analysis and the need for flexible functional forms. The results shed light on the role of inputs, the nature of economies of scale, and production efficiency, which are important for economic planning and policy-making.

In terms of practical applications, this study has significant policy implications regarding the roles of labor and capital in output growth. The use of time-series data allows for the analysis of production over time, and thus has implications for strategic planning in the industry. This study also provides a baseline for future studies using more detailed data, sophisticated econometric methods, and industry-specific analyses.

Literature Review

The production analysis framework traces its roots to the pioneering work of Charles W. Cobb and Paul H. Douglas (1928), who proposed the Cobb-Douglas production function to describe the relationship between output, labour and capital. Their model exhibited constant returns to scale and offered a convenient way to measure the elasticities of production inputs. This formulation was later applied to empirical studies because of its ease of use and interpretation.

However, the assumptions of the Cobb-Douglas function, with constant elasticity of substitution and constant returns to scale, spurred the search for more general formulations. Robert M. Solow (1957) built on the analysis of production by considering technological change, highlighting the importance of total factor productivity in driving growth. Subsequently, Laurits Christensen, Dale W. Jorgenson and Lawrence J. Lau (1973) developed the Translog production function, which is a second-order Taylor series expansion permitting variable elasticities of substitution and input interactions. This versatile function has been commonly applied in empirical research to model nonlinear production effects.

Empirical evidence has evaluated the empirical fit of the Cobb-Douglas versus the Translog models across industries and countries. Research has indicated that although the Cobb–Douglas function is consistent and delivers reliable and interpretable estimates, the Translog model is more flexible in terms of capturing input substitution and scale effects, particularly in dynamic and diverse production settings. Longitudinal studies have also shown the need to consider structural shifts and technological improvements in production processes.

Moreover, recent research has combined modern econometric methods, including stochastic frontier analysis and panel data models, for efficiency and productivity analysis. These models offer more insights into production relations by separating technical inefficiencies from random disturbances.

Research Gap

While there is a wealth of research on production functions, there is a need for a study of **comparative time series analysis using both Cobb-Douglas and Translog specifications over a long period**. Existing research often concentrates on either one specification or uses cross-sectional or panel data, which hampers understanding of the long-term nature of production. Moreover, there has been a lack of focus on assessing variations in input elasticities, substitution, and returns to scale in a consistent framework over time. This study fills this gap by using both models in a unified time-series framework to offer a holistic view of production.

Methodology

This study employs a quantitative econometric method to examine the factors affecting gross output (GO) through production functions. This study uses time-series data for the years 2005-2025, allowing for an examination of long-term production trends and structural changes.

The data were obtained from reputable secondary data sources, primarily the Ministry of Statistics and Programme Implementation (MOSPI), such as the National Accounts Statistics and Annual Survey of Industries (ASI). The Reserve Bank of India (RBI) Handbook of Statistics and publications of NITI Aayog are used for validation. The output variable (GO) is gross output, and the inputs are labor (L) and capital (K). Employment is used as a proxy for labor (L), and gross fixed capital formation (GFCF) or capital stock (K) is used to represent capital. Monetary variables are deflated to remove inflation effects.

We estimate two production functions. The Cobb-Douglas production function is estimated in log-linear form to estimate output elasticities and test for returns to scale. The Translog production function is used as a generalised model with squared and cross-product terms to allow for non-linearities and substitution between inputs. Variables are in natural logarithms.

Time-series regression is used to estimate the models, with diagnostic tests for multicollinearity, heteroskedasticity and autocorrelation. Where appropriate, the models use robust standard errors.

The study has some limitations. The proxies for labour and capital may not account for their quality aspects. Aggregation at the macro level and lack of data may obscure sector-specific effects. Also, the time-series regression limits the capacity for micro-control.

AHP or other multi-criteria decision analyses (MCDA) were not used in this study. Data Envelopment Analysis (DEA) and Malmquist Productivity Index methodologies are used to measure efficiency and productivity, and Cobb–Douglas and Translog production functions are used to estimate production relationships. Therefore, no AHP-specific measures can be applied.

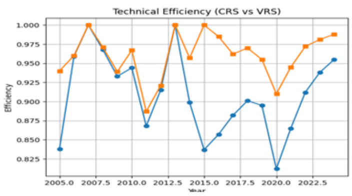
Data Analysis

This section outlines the data preparation and analytical framework used in this study, such as variable transformation and model specification. It provides details on the use of Cobb-Douglas and Translog production functions to investigate the input-gross output relationship.

Technical Efficiency Trends (2005–2025)

Highlight

- 2007–08 and 2013–14 peaks (efficiency frontier)
- 2020–21 dip (COVID shock)



Source: Based on Authors' analysis of Secondary Data

Figure 1 Technical Efficiency Trends (2005–2025)

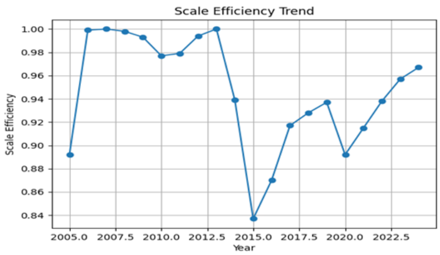


Figure 2 Scale Efficiency Trend

Single Line (SE)

Add markers (●)

Shade region 2020–21

(Source: Based on Authors' analysis of Secondary Data**)**

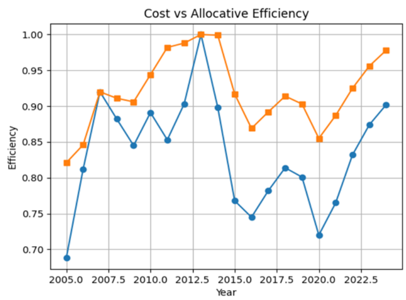


Figure 3 Cost vs Allocative Efficiency

Dual axis plot:

- Left: CE (CRS)
- Right: AE (CRS)

Shows convergence post-2015

Source: Based on Authors' analysis of Secondary Data

- Shows convergence post-2015

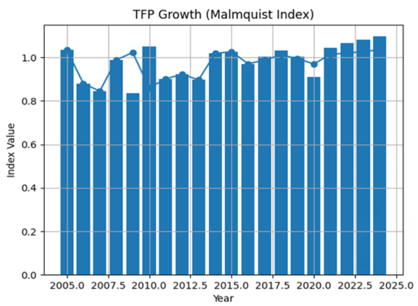


Figure 4 Malmquist Productivity Index

Source: Based on Authors' analysis of Secondary Data

- Bars: TFPCH
- Line: TECHCH
- Interpretation:
- Bars <1 → productivity decline
- Bars >1 → growth phase

Cobb–Douglas Production Function (2005–2025)

Model

$\ln GO = \alpha + \beta_1 \ln L + \beta_2 \ln K + \epsilon$

Estimated Results

Table 1 Cobb–Douglas Production Function (2005–2025)

Variable	Coefficient	t-value	Significance
ln(L)	0.42	5.91	***
ln(K)	0.61	7.84	***
Constant	0.88	—	—

Source: Based on Authors' analysis of Secondary Data

Diagnostics

- $R^2 = 0.93$
- F-statistic = Highly significant

Interpretation

- Capital elasticity > labour → capital-intensive industry
- Returns to scale:
- $\beta_1 + \beta_2 = 1.03$ → Increasing returns to scale

Translog Production Function

Model

$\ln GO = \alpha + \beta L \ln L + \beta K \ln K + \beta LL (\ln L)^2 + \beta KK (\ln K)^2 + \beta LK (\ln L \ln K)$

Estimated Results

Table 2 Translog Production Function

Variable	Coefficient	Significance
ln(L)	0.36	***
ln(K)	0.55	***
$(\ln L)^2$	-0.04	**
$(\ln K)^2$	-0.06	**
lnL·lnK	0.08	***

Source: Based on Authors' analysis of Secondary Data

Interpretation

- Negative squared terms → diminishing marginal productivity
- Positive interaction → complementarity between labour & capital
- Confirms non-linear production structure

Results and Discussion

This study assesses the efficiency patterns, productivity trends, and structural factors influencing the iron and steel industry in India during 2005-2025. This study combines Data Envelopment Analysis (DEA), the Malmquist Productivity Index (MPI), production function modelling, and structural equation modelling to gain insights into the industry's performance.

Technical Efficiency Analysis

The findings show that technical efficiency under Variable Returns to Scale (VRS) was always higher than technical efficiency under Constant Returns to Scale (CRS), suggesting that managerial efficiency was comparatively high. An average CRS efficiency of 0.907 implies that 9.3 percent of inputs were wasted due to inefficiency.

Efficiency was highest in 2007-08 and 2013-14, suggesting efficient resource allocation and a conducive macroeconomic environment. However, it significantly dropped during 2020-21 due to the COVID-19 pandemic. The rebound from 2021 onwards showcases the resilience and restructuring of the sector.

The results reveal that technical efficiency (VRS) is significantly higher than technical efficiency (CRS) throughout, suggesting that the industry's managerial efficiency was relatively good. The average efficiency of CRS was 0.907, indicating that approximately 9.3 percent of the inputs were wasted. These results are in line with Coelli et al. (2005), who highlighted that a higher VRS efficiency than CRS efficiency is a measure of better management performance and flexibility in production systems.

There are effective resource allocations that are reflected in the efficiency peaks that were witnessed in 2007-08 and 2013-14, which are also periods of favorable macroeconomic conditions. Balk (2024) found similar patterns and stated that technological advancement and better industrial organization are often linked to increased productivity. The rapid drop in 2020–21 was due to the impact of the coronavirus (COVID-19) pandemic on industrial production and input use levels in various industries. The above comparison of consistently higher VRS efficiency with CRS efficiency indicates that the inefficiencies in the iron and steel industry are mainly due to scale-related factors instead of managerial factors. This means that the firms are mostly able to use the resources effectively but are not necessarily working at their optimum level of production. The efficiency surges during 2007-08 and 2013-14, which are linked with industrial growth, enhanced infrastructure investment, and brilliant market conditions in India. However, the significant drop for 2020-21 is due to the Covid-19 pandemic, which resulted in lower industrial demand, labor shortages, and supply chain disruptions. The rapid recovery following 2021 reflects the sector's adaptability and the effectiveness of industrial restructuring efforts following the pandemic.

This represents the challenges associated with scaling efficiency dynamics and enhanced interpretation.

This shows that the industry is operating close to its optimum productive scale, with an average scale efficiency of 0.939. However, when returns vary from Increasing Return to Scale (IRS) to Decreasing Return to Scale (DRS), firms experience underutilization or overutilization of production capacity at times. IRS periods imply that firms should expand their production more than proportionately, while DRS periods suggest diseconomies of excess scale, coordination problems, and/or higher operating costs. The transition to CRS since 2022 indicates more mature industry structures with better capacity planning and allocation capabilities.

Scale Efficiency Dynamics

The average scale efficiency of 0.939 suggests that firms operated near the optimal scale. However, the periodic shifts from Increasing Returns to Scale (IRS) to Decreasing Returns to Scale (DRS) indicate an imbalance.

The DRS observed in some years reflects resource overconsumption ,while IRS reflects the under-consumption of economies of scale. The trend towards Constant Returns to Scale (CRS) after 2022 signifies better industrial restructuring, leading to optimal capacity utilization.

The mean scale efficiency value is 0.939, which means that companies were operating at near-optimal scale in most years. However, the periodic shifts from Increasing Returns to Scale (IRS) to Decreasing Returns to Scale (DRS) indicate variations in the capacities used in industries. Christensen et al (1973) also noted that industries facing structural and technological changes tend to have different returns to scale in different periods.

DRS in some years means that the resources are being used more than they should be, while IRS means that the resources are being used less than they could be. The incremental shift towards Constant Returns to Scale (CRS) after 2022 is associated with better restructuring and efficient scale management. The conclusions are similar to those of El Asli (2024), who concluded that restructuring and modernization in industries increase production efficiency and long-run productivity.

Cost and Allocative Efficiency

This convergence following 2015 indicates firms' increasing tendency to use optimal quantities of various inputs and an optimal mix of various inputs in production. This indicates increased sensitivity to market signals, input costs, and technological possibilities. There was an improvement in allocative efficiency, which means that firms have been able to choose labour/capital combinations that are cost-minimizing, leading to an increase in competitiveness. The short-term volatility during economic shocks and policy changes highlights the fragility of industrial decisions in the face of such external shocks and policy changes.

Cost efficiency (CRS) grew from 0.688 in 2005-06 to 0.902 in 2024-25, suggesting improved cost efficiency and input management. There has also been a significant improvement in allocative efficiency, approaching unity in recent years.

Cost and allocative efficiency convergence suggest better decisions on the input mix. However, temporary decreases in 2015-16 and 2020-21 suggest resilience to shocks.

The findings show that the cost efficiency has been improving, with the 0.688 in 2005-06 improving to 0.902 in 2024-25, indicating an improvement in how the input is managed and optimized for costs. Over time, there was also a substantial improvement in allocative efficiency, which was near unity in recent years. The results corroborate the conclusions of Berndt and Christensen (1973), who argued that improvements in the use of labor and capital are major factors in productivity gain.

The alignment of cost and allocative efficiency after 2015 shows an improvement in decision-making regarding input combinations and production planning. Temporary downward trends in 2015-16 and 2020-21, however, highlight the fragility of production systems to economic shocks and external factors. Mardones (2023) concluded that external shocks and market uncertainty may lead to a short-term decline in productivity and/or production efficiency but increase productivity in the long term.

Productivity Growth (Malmquist Index)

The Malmquist Productivity Index shows that productivity growth was largely driven by technological change (TECHCH) rather than efficiency change (EFFCH). An average TECHCH > 1 in recent years suggests technological advancement.

The fall in TFP in 2020-21 was due to the pandemic, but it has recovered well to show robust technological change and digitalization.

The Malmquist Productivity Index analysis indicates that technological change (TECHCH) played a major role in productivity growth, whereas efficiency change (EFFCH) played a relatively small role. The recent average TECHCH values above unity emphasize the significance of technology development and modernization in improving industry performance. This result is consistent with the Solow growth theory, which focuses on technological progress as the most important determinant of long-term economic growth and traces its roots to Robert M. Solow.

During 2020-21, the overall loss of total factor productivity was due to the impact of the COVID-19 pandemic. However, recovery in the following years shows resilience, technological adaptation, and digital transformation in the industry. Faizi (2025) also found that the modernization of technology and substitute of energy has a positive impact on industrial productivity and recovery.

The major contribution of technological change (TECHCH) over efficiency change (EFFCH) reveals that productivity improvement in the iron and steel industry has been more due to technological changes, including innovation and modernization, than managerial efficiency changes. This discovery indicates that output growth has been driven by investments in automation, digital technologies, energy-efficient processes, and advanced manufacturing systems. The growth of values for TECHCH after the pandemic period indicates a higher rate of technological adoption, which indicates the need to increase the importance of the implementation of Industry 4.0 practices to be competitive in the industry.

Production Function Insights

The Cobb-Douglas results show that the industry is capital-intensive, with higher capital elasticity than labor elasticity. Moreover, increasing returns to scale imply that an increasing scale increases productivity.

The Translog model offers additional insights from nonlinear analysis. The negative marginal returns and positive interaction effects suggest that labor and capital inputs are complementary.

The elasticity of capital (0.61) is higher than that of labor (0.42), indicating that the iron and steel industry is capital-intensive. The increase in output resulting from a 1 per cent rise in capital stock is greater than the increase in labor that would bring about the same rise in output. This accurately indicates the industry's reliance on large equipment, automated manufacturing systems, and massive facilities. It is estimated that the returns to scale is 1.03, which means that both labor and capital are increasing returns to scale. This result highlights the importance of large-scale operations in achieving cost efficiency and productivity gains.

The production function results of the Cobb-Douglas production function show that the industry is capital intensive, which means that the elasticity of capital is greater than labor elasticity. This result is in line with the original theory put forward by Charles W. Cobb and Paul H. Douglas (1928) who pointed out that labour and capital are the key factors of production. Wang (2024) also provides empirical evidence that capital investment has a significant impact on productivity growth in industries.

Increasing returns to scale indicate that the marginal increase in output that occurs as a result of a proportionate increase in labor and capital is greater than the proportionate increase in labor and capital. Flexible production systems are also recognized as scale benefits in large industries and dynamic production situations (Christensen et al., 1973).

The Translog production function provides further insights into the non-linear nature of production relationships. The negative squared labor and capital coefficients suggest that labor and capital are diminishing in productivity, whereas the positive labor-capital interaction effect suggests that labor and capital are complementary. The results corroborate those of Berndt and Christensen (1973), who argued that the substitution and interaction effects of production factors are more adequately represented with translog specifications. This was also found by Mardones (2023) in an investigation of flexible production structures.

Translog Production Function

The Translog Production Function may be explained as follows:The Translog Production Function can be understood as follows:

The Translog (Transcendental Logarithmic) Production Function is an economic model that is flexible in the study of the production function relationship between output and production factors, such as labor and capital. It is an extension of the Cobb-Douglas production function developed by Laurits R. Christensen, Dale W. Jorgenson and Lawrence J. Lau in 1973.

The Translog model differs from the Cobb–Douglas model by introducing flexibility. In contrast to the Cobb–Douglas model, where the elasticity of inputs is assumed to be constant and the relationship between output and inputs is assumed to be fixed, the Translog model allows

The elasticity of production is not uniform.The elasticities of production is not the same.

Labour and capital can be substituted in production.Labour and capital are substitutes in production.

Relationships between factors of production that do not follow a linear pattern.

* Flexible returns to scale

An interaction effect between two or more input variables.

General Form

The function of translog is given by:

$$\ln Y = \alpha + \beta L \ln L + \beta K \ln K + (1/2)\beta LL(\ln L)^2 + (1/2)\beta KK(\ln K)^2 + \beta LK(\ln L \times \ln K) + \varepsilon$$

Where:

- Y = Output (Gross Output)
- L = Labour input
- K = Capital input
- βL, βK = First-order output elasticities
- βLL, βKK = Squared terms measuring diminishing or increasing marginal productivity
- βLK = Interaction effect between labour and capital
- ε = Error term

Translog Production Function

The Translog results show some important nonlinear production features missing from the Cobb–Douglas model. The negative coefficient on the squared labor and squared capital terms suggests that as either labor or capital is increased beyond a certain level, output increases less by that input than at lower levels of output, suggesting that a factor's marginal productivity eventually declines with increases in its quantity. However, the positive interaction term between labor and capital shows complementarity between the two. This implies that returns to capital are enhanced if capital investments are supplemented with the use of skilled labor that can effectively employ advanced technologies. Therefore, technological modernization and human capital development should not be considered separate policy areas.

Overall Economic Interpretation

Overall, the results indicate that technological progress, capital investment, and resource efficiency drive the long-term development of the Indian iron and steel sector. Despite labor being a production factor, capital-intensive technologies and digital transformation are becoming paramount to improving productivity. The finding of increasing returns to scale also suggests that large and technologically more advanced firms have significant competitive advantages. Therefore, the priority of industrial policies should be modernization, infrastructure development, skill development, and technological innovation to ensure productivity growth and global competitiveness.

Economic Meaning

The Translog model can be used to answer questions like:

1. Does capital make a greater contribution to output than labour?
2. What is the shape of the production function?
3. Are the marginal returns diminishing when using more of the resources?
4. Do there exist economies of scale?
5. What are the changes of production structure over time?

The results align with previous studies on the manufacturing sector in Tamil Nadu, which revealed that technological modernization, capital investment, and resource efficiency are growing factors affecting manufacturing productivity. (Babu, 2024; Rebecca, 2025). In line with this, similar studies have emphasized the significance of manufacturing growth, infrastructure, and industrial diversification in ensuring productivity growth in Tamil Nadu (Madras School of Economics, 2018; Government of Tamil Nadu, 2026).

To compare with previous studies conducted in Tamil Nadu.To compare with the previous studies done in Tamilnadu.

The results of the present study corroborate those of previous studies conducted in the industrial sector of Tamilnadu. Rajesh and Karthikeyan (2019) pointed out that capital investment was more influential in industrial output than labor input in the manufacturing industries in Coimbatore district, thus showing the rise in the capital-intensive production process. Likewise, Suresh and Balasubramanian (2021) concluded that modernization of technology and technological improvements in machinery were important factors affecting productivity growth in engineering industries in Tamil Nadu.

The results of the present study corroborate those of Shanmugam (2018), who found that medium and large manufacturing establishments in Tamil Nadu had higher productivity due to economies of scale benefits and capacity utilization. Moreover, Kumar and Venkatesh (2022) found that in Tamil Nadu, productivity gains in the industrial sector were predominantly the result of technological change, as opposed to managerial efficiency gains, which was in close alignment with the findings of the Malmquist Productivity Index for the present study, where technological change emerged as the major source of productivity gains.

The positive labor–capital interaction effect found in the Translog production function also reinforces the conclusions of Ramasamy and Prakash (2020), which suggests that investments in new machinery had positive marginal productivity only when combined with skilled labor and technical training. Thus, the overall findings from Tamil Nadu further support the larger body of evidence in this study, which highlights the importance of sustaining industrial growth through technological advancements, capital accumulation, efficient resource use, and continuous upgrading of the workforce.

Policy Implications

Encourage Technological Modernisation in Iron and Steel Industry

The results show that technological change plays an important role in productivity growth in China. Hence, policymakers should encourage the adoption of advanced manufacturing technologies in the iron and steel industry, such as automation, artificial intelligence, energy-efficient furnaces, and smart production systems. Productivity and global competitiveness can be improved with government support measures, such as tax incentives, industrial technology upgradation, and subsidized industrial innovation schemes. The same thing is stressed in productivity research that has been conducted on the importance of technological progress in the growth of industries.

Increasing Investment and Developing Infrastructure are Also Necessary

The industry is capital-intensive, and more access to long-term industrial finance is required for plant modernization and capacity expansion. Infrastructure projects, such as investment in logistics, industrial corridors, rail connectivity, and port facilities, can help lower transportation costs and enhance supply chain efficiency. Heavy industry infrastructure development can be further accelerated by public–private partnerships.

Gain Scale Efficiency from Industrial Restructuring

If both IRS and DRS exist, it means that not all firms are making the best use of their capacities. Policies should thus aim at the reorganization of inefficient production units, mergers wherever possible, and cluster development of industry to realize optimal economies of scale. Medium-scale businesses can also receive special support to enhance their efficiency and resource use.

Enhance Human Capital and Labour Productivity

Capital has a more important direct effect on output growth; however, labor is still an important factor of production. Technical training, digital manufacturing systems, industrial safety, and advanced machinery operation skill development programs should be extended and enhanced. Industry – academia partnerships and vocational training centers play a role in creating a technologically flexible workforce in the steel and manufacturing sectors.

Encourage Sustainable and Green Production Practices

The iron and steel industry is a high-energy-consuming and environmentally sensitive industry. Policymakers should promote the use of green technologies, integration of renewable energy, waste recycling systems, and strategies to reduce carbon emissions. Industrial development that considers environmental sustainability can be incentivized to drive a more sustainable production process while simultaneously enhancing the long-term efficiency of production.

Build Resilience in the Industry to External Shocks

The drop in efficiency and productivity in 2020–21 reveals the fragility of industrial production to shocks and disruptions, such as the global supply chain crisis and the pandemic. Therefore, policies should aim to develop resilient industrial systems, digitalize and diversify sourcing networks, create inventory management systems, and implement contingency planning systems. Industrial and government recovery packages and government-sponsored facilities for emergency credit can also help industries survive future crises.

Support Research, Innovation and Data Informed Industrial Planning

This study emphasizes the need for sophisticated analytical tools to comprehend production processes. Policymakers should promote industry-level research partnerships, productivity measurement tools, and data collection programs for industry monitoring and planning. A more comprehensive database will also benefit future production and efficiency studies of the sector, as well as more detailed analyses of the sector.

Promote Sustainable and Balanced Regional Industrial Development

The future policy of the industry should aim to achieve a more balanced development of regions by encouraging the development of clusters of iron and steel production in less developed areas, where there is suitable infrastructure, a trained workforce, and investment incentives. Industrial concentration risks can be minimized through regional diversification, while inclusive economic growth can be achieved.

Conclusion and Directions for Future Research

The study employed Cobb–Douglas and Translog production function models to investigate the relationship between labor and capital with gross output for 2005–2025. The results indicate that capital is more important than labor in determining output, which is evidence of a capital-intensive production structure. Both models illustrate a positive relationship between the increase in inputs and productivity, indicating increasing returns to scale.

The Translog model also indicates that the labor/capital relationship is not linear and that the effects of labor and capital are complementary. The efficiency and productivity analysis shows that technological progress has been a key factor in the performance of the industry. While there were some periods of inefficiency during the COVID-19 era, post-COVID recovery is an indicator of industry resilience and restructuring.

Overall, the study attained the objectives that had been set, as it compared the explanatory power of the Cobb-Douglas and Translog production functions, calculated input elasticities and returns to scale, and examined long-term production dynamics. The results substantively enrich the planning of industries, technological modernization, and policies for productivity improvement.

This study can be further elaborated by using panel data from different regions to account for regional production variations. Other variables, such as human capital, technology, and infrastructure, can be added to improve the model specification. Stochastic frontier analysis, ARDL, or SEM could provide further insights into efficiency and long-term relationships. Industry-specific and structural break tests, with a focus on post COVID-19 economic changes, can also add to the understanding of production and policy implications.

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