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RESEARCH ARTICLE

Analysing the cost structure of construction sectors considering carbon emission factors

Modenisha U[1], Ritha W[1*], Sasitharan Nagapan[2]

Abstract
As a major engine of economic growth and development, developing nations must have a thriving manufacturing sector. This is due to the fact that the industry makes a nation more competitive, increases productivity, and generates jobs. By expressing cost as a function of six inputs, including labour, output, fixed cost, fuel consumed, materials used, and carbon emission, the study aimed to estimate the Translog cost function for India's manufacturing sector using cost factor share equations. With a 99.5% R^2 value of 0.995 for the cost variation using the chosen inputs, the results demonstrate a strong model fit. Among the other input values, total output, fuel consumption, and fixed capital were the most important cost drivers. The robustness of the results was further supported by the statistical significance of the estimated coefficients with *p-values* less than 0.01. The PCA has successfully reduced multicollinearity, which is frequently seen in Translog models with few observations. In order to improve the sustainability of these manufacturing industries, this study assists policymakers in designing carbon policies and optimizing cost structures.

Keywords: Trans-log cost function, Carbon emission, Cost structure, Manufacturing industries, Construction sectors, Cost shares, Production economies.

关键词: 超越对数成本函数、碳排放、成本结构、制造业、建筑业、成本分摊、生产经济。

Introduction
Any nation's economic growth and development are greatly aided by the manufacturing sector, which creates jobs, increases a nation's competitiveness, and fosters productivity. Because of the way their economies are structured, many developing nations want to become highly industrialized, but their industrial sectors are not strong. A framework of flexibility and strategic development that extends beyond the economic realm to social and sustainable dimensions is produced by the manufacturing sector's ongoing evolution through the pursuit of efficiency and adaptability. The facts demonstrate that the trade or service sector now dominates many nations, despite a recent debate regarding the continued importance of the industrial sector in economic growth. The lack of consensus does, in fact, reflect our inadequate comprehension of the manufacturing sector's significance, especially for middle-income economies. The well-established patterns of structural change in various industries are widely acknowledged as empirical realities, in contrast to the predictions that emerge from a specific theory. Developing countries need a strong industrial sector to drive income growth in their pursuit of progress. One of the most important factors influencing a country's economic development is the effectiveness of its industrial sector (Afin *et al*., 2025).

India's economy, industrialization, and energy consumption are making its contribution to global climate change increasingly crucial. Even though per capita energy consumption is lower than in the developed world, it is predicted to increase significantly, contributing to climate change. According to the Ministry of Environment, Forest, and Climate Change (MoEFCC, 2015), India has associated the mitigation potential targets with diminishing the discharge intensity from its economic growth by 33 to

[1]PG & Research Department of Mathematics, Holy Cross College (Autonomous), Affiliated to Bharathidasan University, Tiruchirapalli-620002, India.

[2]Faculty of Civil Engineering and Built Environment, Universiti Tun Hussein Onn Malaysia, Johor- 86400, Malaysia.

***Corresponding Author:** Ritha W, PG & Research Department of Mathematics, Holy Cross College (Autonomous), Affiliated to Bharathidasan University, Tiruchirapalli-620002, India, E-Mail: ritha_prakash@yahoo.co.in

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35% by 2030 relative to the 2005 level. This will happen because of advancements in technology and the availability of affordable foreign funding. As India's economy and industrial base add to bystander growth, the demand for industrial products is rising. From 1990 to 2020, Indian policymakers have focused on the economy's typical yearly growth share of 7.75% (India Economic Survey, 2021). Being the second-largest sector after the services sector and accounting for 25.02% of the Indian economy in 2020, the industrial division undoubtedly plays a significant role in the country's remarkable progress record. India generated 100 million jobs and made up 25% of the economy, according to Asia's Industrial Transformation (Felipe, 2018). Additionally, it was observed that industrial sector employment increased across the four ASEAN nations, with China and India holding a dominant position (Raza *et al*., 2024).

Principal Component Analysis (PCA)

A multivariate method called PCA examines a data table where observations are represented by a number of quantitative dependent variables that are correlated with one another. Its objective is to extract the key information from the table, represent it as a collection of new orthogonal variables known as principal components, and use points on maps to show how similar the variables and observations are. Cross-validation methods like the jackknife and bootstrap can be used to assess the CA model's quality. For handling qualitative variables, PCA can be generalized as correspondence analysis, and for handling heterogeneous sets of variables, it can be generalized as multiple factor analysis (Abdi *et al*., 2010). A flexible statistical technique for distilling a cases-by-variables data table to its key elements, or principal components, is principal component analysis. A small number of linear combinations of the original variables that account for the majority of the variance in all the variables are known as principal components. Using just these few key elements, the method yields an approximate representation of the original data table (Greenacre *et al*., 2022).

Literature Review

The adoption of sustainable manufacturing practices has become imperative (Santeliz & Contreras, 2014; Yong, 2021). Despite having a positive effect on a nation's economic growth, the manufacturing sector is not without its difficulties. There are several detrimental effects of production processes on the environment, such as waste generation that degrades soil quality, fine particle emissions, chemical contaminants, and air and water pollutants. These effects, which endanger ecosystems and public health, are among the main issues the industry faces. Striking a balance between industry and conservation is crucial to reducing these effects. 31% of the 36.8 million metric tons of carbon emissions produced worldwide in 2021 came from the industrial sector (IEA, 2024a). The World Bank (2024a) claims that greenhouse gas emissions—of which carbon dioxide makes up the largest portion—are primarily to blame for the significant effects of climate change. Numerous authors have written about studies on sustainable manufacturing, showing how sustainability can assist businesses in improving their operational efficiency and environmental results. The modern world is realizing that a new economic paradigm for production and consumption needs to take social and environmental effects into account. There is growing pressure on industries to disclose the social and environmental effects of their operations in a transparent manner. In this regard, sustainable manufacturing needs to be both socially and financially responsible while reducing adverse effects on the environment and the use of energy and natural resources. For this reason, the idea of sustainable manufacturing is becoming more and more popular among organizations and researchers, particularly in the industrial sector (Abdul-Rashid *et al*., 2017).

The marginal cost of supplying potable water was estimated using a generalized translog (GT) cost, and the implications for more effective, equitable, and income-adequate tap water tariffs in Tunisia, as well as a new pricing model for potable water, were examined. Elasticity of substitution, own-price elasticity, and cross-price elasticity were all taken into account when estimating the transcendental logarithmic cost function. The cost function is estimated using four factor inputs: labor, capital, energy, and materials. The findings show that the largest portion of the cost is attributed to materials. Additionally, there is little elasticity in the substitution of materials for energy and capital. The own-price elasticities show that while the demand for other inputs fluctuates with price, the demand for materials is least sensitive to changes in its own price. The cross-price elasticities demonstrate the substitutability of labor, capital, and energy. The existence of economies of scale is demonstrated by the output elasticity of cost (Amor 2022). In order to investigate the food industry in Pakistan to determine the transcendental logarithmic cost function, applying Zellner's iterative methodology, a strong labor-capital substitution was demonstrated by the estimation of Allen's partial ES, output elasticities of cost, cross-price elasticities, and own-price elasticities. The study showed a rise in the replacement of capital with labor in the food processing sector. Although energy and capital are good substitutes, there is much less substitutability between material and energy and between material and capital (Hussain *et al*., 2020).

India has a sizable and quickly expanding cement, lime, and plaster industry. For this reason, both academics and policymakers are very concerned about how efficiently this industry operates. A thorough examination of the industry's cost structure describes the nature of technological advancement and its effects on factor incomes in this sector, economies of scale, elasticity of substitution between factors, and allocative efficiency were among the topics covered. The production function has usually been the focus of traditional analyses of an industry's production efficiency. The production function of a company, or more precisely its production frontier, indicates the highest output that can be generated from amounts of a given set of inputs. Accordingly, the lowest cost involved in producing any level of output is indicated by a firm's cost function (Jah *et al*, 1991).

The study set out to examine the economic advantages and production costs of potato cultivation in Iran's Ardabil province. In order to accomplish this, 183 potato farmers were chosen at random and asked to participate in an interview and questionnaire to share their thoughts on the costs and advantages of production. To improve the data, a field study was also considered. The Translog cost function, Wald test, and Chi-squared measures were used to analyze the gathered data. (Moghaddam *et al*., 2021).

Mathematical Model

Notations

C : Total cost

Y : Total output

PC : Principal components derived from standardized log transformed input variables.

PC_i : ith principal component

α_0 : Base level log-cost (intercept)

α_y : Coefficient of $\ln y$

α_i : Coeff of principal components

γ_i : Coefficients of interaction terms $\ln y \cdot PC_i$

λ_{ji} : Loading (weight) of variable x_j in ith PC

S : Standardized PCA which is subtracting the mean and dividing by the standard deviation.

Problem Description

$$\ln C = \alpha_0 + \alpha_y \ln Y + \sum_{i=1}^{k} \alpha_i PC_i + \sum_{i=1}^{k} \gamma_i (\ln Y \cdot PC_i)$$

Where $PC_i = \sum_{i=1}^{k} \lambda_{ji} \cdot S(\ln x_j)$

Regardless of their initial scales or units, this standardization guarantees that every input price variable makes an equal contribution to the calculation of the principal components. As a result, more significant and reliable principal components (PC_i) for the Translog cost function can be produced by the PCA, which can successfully identify latent factors that represent the common variation across the input price structure. Therefore, the intrinsic correlations and co-movements among the input prices which are then utilized as independent variables in our cost function estimation are more accurately reflected by the standardized principal components.

Shephard's Lemma

The original input variables' marginal cost shares were estimated using Shephard's Lemma in the PCA-transformed space. Because the Translog cost function was calculated using principal components rather than the original input logs directly, the cost share expression is an approximation rather than an exact derivative. By projecting the cost contribution of each input onto the principal components, this linear combination ignores higher-order interaction terms that would be present in a full Translog specification using original variables.

$$\frac{\partial \ln C}{\partial \ln x_j} \approx \sum_{i=1}^{k} \lambda_{ji} \cdot \alpha_i$$

The initial step is to estimate the translog cost function using the ASI data on the manufacturing of cement, lime, and plaster in order to manage the fluctuations and comprehend the cost structure of the construction sector to improve its efficiency. This analysis is conducted taking into account the following key factors: Total Inputs, Total Output, Fuels Consumed, Materials Consumed, Fixed Capital, and Carbon Emission values. Eleven years, from 2012 to 2023, were covered by the data. A Python code was created to perform the analysis and estimate the final solutions.

Result

The PC values' coefficient terms terms from the Table 1, clearly show that they are statistically significant and positive. When the principal components with a positive coefficient score increase, the overall cost also increases. These high statistical

Table 1: The PCA Translog estimations

R-squared		*0.995*					
		coef	*Std err*	*t*	*P>|t|*	*[0.025*	*0.975]*
const		17.8041	0.005	3885.233	0.000	17.793	17.815
PC1	x_1	0.0712	0.002	33.427	0.000	0.066	0.076
PC2	x_2	0.0646	0.005	13.051	0.000	0.053	0.076
PC3	x_3	0.0354	0.007	4.965	0.002	0.019	0.052

values thus provide a clear explanation of the significance of cost variations in the construction sector. The Sheppard's lemma gave the approximate marginal cost shares for the given input terms, showing how the original input structures affect the costs. The interpretation of the PC components led to the determination of the principal loading. The total inputs, outputs, materials, and fuel consumed all affect the x_1 values. These loadings show the overall resource consumption and production scale. x_1 values represent the overall operational scale or the production intensity. This suggests that a large-scale operation is the result of a positive x_1 showing a high resource input and output. With a positive loading on fixed capital and carbon emissions, the x_2 displayed the relationship between capital investment and emissions. Here, a carbon-intensive structure is evident. A trade-off between capital, energy, and carbon consumption was suggested by x_3 , which took into account fuel consumption, carbon emissions, and a negative loading on fixed capital. This indicates that businesses that depend on capital assets may use more energy and produce more carbon emissions.

The results of regression analysis, which serves as a significant predictor of total cost and uses x_3 as the marginal cost, show statistically significant results. The positive x_1 coefficient, which indicates an increase in production intensity, suggests that overall costs have gone up. The environmental relevance of fixed capital efficiency is delivered by x_2 , which has high capital and emission costs. The model shows no heteroscedasticity, according to the Breusch pagan test. The PCA model exhibits better estimation reliability and less multicollinearity. This principal component analysis (PCA) shows how the initial input variables combine to create the new principal components. A one-unit increase in PC1 corresponds to a 0.0712-unit increase in the overall cost, as indicated by the PC1 value of 0.0712. With a coefficient of 0.0646, the PC2 capital-carbon correlation also affects cost. The PC3, which represents fuel-emission reliance, also made a significant contribution, albeit with a smaller value of 0.0354. This lower figure shows that even with lower capital expenditures, energy-intensive operations are expensive.

With a cost share of 5.89%, fixed capital is the largest contributor to the overall cost. Fuel coat and carbon emissions come in second and third, respectively, at 5.00% and 3.47%. These cost shares show that energy use and capital intensity are the main causes. From Table 2, the obtained cost-share values are interpretable from an economic perspective and are positive.

Table 2: Marginal Cost Share Estimations

Input values	*Estimated cost shares*
Fixed Capital	0.0589
Fuels Consumed	0.0500
Total Output	0.0353
Carbon Emission	0.0347
Total Input	0.0339
Material Consumed	0.0303

Discussion

As a major engine of economic growth and development, developing nations must have a thriving manufacturing sector. This is due to the fact that the industry makes a nation more competitive, increases productivity, and generates jobs. By expressing cost as a function of four inputs—labor, electricity, water, and petroleum products—the study aimed to estimate the Translog cost function for Kenya's manufacturing sector for 2019 as well as the cost factor share equations. It was assumed that the Cobb-Douglas type was the production function. An estimate of the Translog cost function was made using the Taylor series expansion. Using STATA, generalized nonlinear least square estimation techniques were used to estimate the parameters for the different restricted forms of the cost functions. The result showed insignificance (Thuo *et al*., 2021).

Conclusion

This study examined the cost structure and input-output dynamics with an estimated marginal cost shares in the context of industrial production using a PCA-based Translog cost function framework that included Shephard's Lemma. This approach successfully highlighted the economies of scale and the dominant cost-driving role of CO2 emissions and showed significant results. The principal component analysis effectively managed the multicollinearity of the model and the intricate interactions between input-output levels. The methodology shows how robust the analytical techniques can still produce valuable and directional insights even with the existence of data constraints, even though the results should be interpreted cautiously due to the small dataset and PCA-induced results. This methodology opens the door for future studies with larger data sets and makes a significant contribution to cost modeling, the convergence of production economies, and improved environmental impact assessment. In order to achieve sustainable production, it is imperative to control carbon emissions and optimize resources at a reasonable cost. Human livelihood is improved by more intelligent industrial practices that incorporate important cost drivers and strategies.

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