

Review

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A Review of Industrial Economic Structure and Efficiency from a Statistical Perspective

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Abstract: This paper provides a comprehensive review of industrial economic structure and efficiency through the lens of statistical methodologies. It systematically discusses key concepts such as technical, allocative, and scale efficiency, and critically evaluates widely used measurement techniques including Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). The paper further explores a broad spectrum of statistical tools — such as descriptive statistics, multivariate analysis, time series and panel data models, as well as spatial statistics and geographically weighted regression — and their applications in analyzing industrial dynamics. Empirical studies illustrating variations across different industries and regions are summarized, highlighting the importance of data quality and processing methods. The integration of traditional statistical approaches with emerging machine learning techniques is also examined, pointing toward future research directions. Finally, the study reflects on the practical implications for policy and industrial development, emphasizing both the strengths and limitations of statistical perspectives in industrial economics research.

Keywords: industrial economic structure; economic efficiency; Data Envelopment Analysis; Stochastic Frontier Analysis; spatial statistics; machine learning

1. Introduction

The analysis of industrial economic structure and efficiency plays a crucial role in understanding the dynamics of economic development and the optimal allocation of resources within an economy. Industrial economic structure generally refers to the composition, organization, and distribution of various sectors and industries, which collectively determine the economic landscape and competitiveness of a region or country. Changes in the industrial structure often reflect broader socioeconomic transformations such as technological advancement, policy shifts, and globalization impacts. Efficiency, as a complementary concept, concerns the ability of industries to utilize resources effectively to maximize output while minimizing waste and costs. Understanding efficiency at both the micro (firm-level) and macro (industry or economy-wide) scales is essential for guiding economic policies aimed at sustainable growth.

From the perspective of statistics, the study of industrial economic structure and efficiency benefits immensely from quantitative analysis methods that allow for rigorous measurement, modeling, and interpretation of complex economic data. Statistical tools, including descriptive statistics, multivariate techniques, time-series and panel data models, as well as advanced methods such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA), facilitate the evaluation of industrial performance and the

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identification of structural changes over time. These methods enable researchers to uncover underlying patterns, assess productivity differences across industries, and evaluate the impact of various factors on economic efficiency [1].

This review synthesizes existing research and methodological approaches used in the statistical analysis of industrial economic structure and efficiency. By highlighting key concepts, measurement techniques, and empirical findings, the review aims to provide a comprehensive foundation for future research and practical applications in economic planning and policy formulation. Through an integrated statistical perspective, this work seeks to contribute to a better understanding of how industrial economies evolve and how efficiency improvements can be effectively promoted.

2. Industrial Economic Structure: Definitions and Key Concepts

The industrial economic structure is a critical framework for understanding the composition and functional distribution of industries within an economy. It reflects how resources such as labor, capital, and technology are allocated across primary (agriculture, mining), secondary (manufacturing, construction), and tertiary (services) sectors. The classification of industrial structure serves as a key indicator of economic development stages and transformation dynamics. For example, a shift from an agriculture-based economy to manufacturing and then services typically characterizes economic maturation and structural upgrading.

The evolution of industrial structure is influenced by a combination of endogenous and exogenous factors. Technological innovation often acts as a primary driver, enabling new industries to emerge and older ones to become more efficient. Globalization facilitates resource reallocation through trade and investment, while changing consumer preferences alter demand patterns. Additionally, government policies, such as industrial subsidies and trade regulations, play an instrumental role in shaping structural adjustments. The process of structural transformation not only affects sectoral shares but also directly impacts overall economic efficiency and growth potential [2].

Measuring and analyzing industrial structure requires a set of well-defined quantitative indicators that capture sectoral contributions and dynamics. Commonly used indicators include output share, employment share, value added, and productivity ratios. These metrics provide multifaceted insights into the scale, performance, and efficiency of industries. Table 1 summarizes key industrial economic structure indicators along with their definitions and economic interpretations.

Table 1. Key Indicators for Measuring Industrial Economic Structure.

Indicator	Definition	Economic Implication
Output Share	The proportion of total economic output attributed to a specific industry	Reflects the economic weight and sectoral dominance
Employment Share	The percentage of total workforce employed within an industry	Indicates labor allocation and structural employment patterns
Value Added	Net output produced by an industry after deducting intermediate inputs	Measures sectoral contribution to GDP and economic value
Productivity Ratio	Output produced per unit input (e.g., labor or capital productivity)	Assesses efficiency levels and technological progress

Statistical methods are indispensable in analyzing these indicators and interpreting the industrial structure comprehensively. Descriptive statistics serve as the foundation by summarizing sectoral data and revealing basic patterns. More advanced multivariate methods, such as cluster analysis and principal component analysis, enable identification of structural similarities and latent factors affecting industrial composition. Time-series and panel data models are frequently utilized to track the dynamic evolution of industrial

structure, allowing for causal inference and policy evaluation. Additionally, spatial statistical techniques help explore regional disparities and industrial agglomeration effects, which are increasingly relevant in the context of regional economic planning.

In summary, the combination of well-established economic indicators and sophisticated statistical methodologies provides a robust framework for understanding the industrial economic structure, its drivers, and its implications for economic policy and development strategies.

3. Efficiency in Industrial Economics: Concepts and Measurement

3.1. Definitions of Economic Efficiency

Economic efficiency in industrial economics is a multidimensional concept reflecting how well resources are utilized to achieve maximum productive output. The concept is generally decomposed into three interrelated dimensions: technical efficiency, allocative efficiency, and scale efficiency. Technical efficiency refers to a firm's capacity to produce the highest possible output with a given set of inputs or, equivalently, to minimize inputs for a certain output level. This dimension captures operational performance and resource wastage at the firm level. Allocative efficiency goes further by considering the input mix relative to input prices, indicating whether the firm's resource allocation minimizes production cost. Thus, allocative efficiency integrates market conditions and economic rationality into the efficiency assessment. Scale efficiency addresses whether the firm operates at an optimal production size, such that it fully exploits returns to scale — avoiding inefficiencies due to suboptimal firm size. Collectively, overall economic efficiency is achieved when firms are simultaneously technically, allocatively, and scale efficient [3].

3.2. Efficiency Evaluation Metrics

Evaluating efficiency quantitatively requires specific metrics. The most common measure is the efficiency score, which typically ranges from zero to one, where one signifies full efficiency. This score represents the relative distance of a firm from the efficient frontier constructed by best-performing firms. Additional metrics such as marginal returns to inputs provide insight into the productivity impact of incremental input changes. Returns to scale indicate whether expanding production leads to proportionate increases in output. Analysis of input redundancies (excess use of inputs) and output shortfalls (underperformance in outputs) is also valuable for diagnosing inefficiency sources. These indicators allow policymakers and managers to pinpoint inefficiency causes and target improvements effectively [4].

3.3. Common Statistical and Econometric Methods

In the industrial economics literature, two methodological frameworks predominate for measuring efficiency: Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA). DEA is a non-parametric, linear programming-based technique that empirically constructs an efficient frontier from observed input-output data without requiring assumptions about the functional form of the production technology. It can handle multiple inputs and outputs simultaneously, evaluating each decision-making unit relative to the best performers. However, DEA treats all deviations from the frontier as inefficiency, rendering it sensitive to measurement errors and outliers, and unable to separate statistical noise from inefficiency effects. SFA, by contrast, is a parametric econometric method that estimates a stochastic production frontier, explicitly decomposing the error term into inefficiency and random noise components. This decomposition enables SFA to account for measurement errors, statistical noise, and environmental shocks that can affect firm performance. Nevertheless, SFA requires specifying a functional form for the production function (e.g., Cobb-Douglas or Translog), and its estimation involves more complex maximum likelihood procedures.

Table 2 below presents a comparative summary of DEA and SFA methods, highlighting their key characteristics, advantages, disadvantages, and typical application contexts.

Table 2. Comparative Overview of Efficiency Measurement Methods in Industrial Economics.

Method	Characteristics	Advantages	Disadvantages	Typical Applications
Data Envelopment Analysis (DEA)	Non-parametric; empirical frontier construction	No functional form assumption; suitable for multiple inputs/outputs	Sensitive to outliers and noise; all deviations interpreted as inefficiency	Benchmarking in manufacturing, service industries, and public utilities
Stochastic Frontier Analysis (SFA)	Parametric; decomposes error term into noise and inefficiency	Accounts for noise; supports statistical inference and hypothesis testing	Requires functional form assumptions; estimation complexity	Agricultural economics, energy sectors, and industries with stochastic influences

3.4. Applications of Statistical Methods in Efficiency Analysis

Empirical studies demonstrate diverse applications of DEA and SFA. DEA has been extensively employed in manufacturing sectors to identify firms with operational inefficiencies by benchmarking against industry leaders. It facilitates diagnosis of resource wastage such as excess labor or capital, enabling targeted interventions. In public utilities and service industries, DEA assists regulators in performance monitoring and incentive design. SFA, meanwhile, is widely applied in agricultural economics to evaluate farm-level efficiency while explicitly modeling environmental factors and random shocks affecting productivity. Energy sector analyses often employ SFA to distinguish inefficiency from external disturbances in power generation and distribution. Furthermore, both methods are frequently integrated with statistical tools such as regression analysis, hypothesis testing, and panel data econometrics to validate results and draw policy-relevant conclusions. The combined approach enhances robustness and aids managerial decision-making in complex economic environments [5,6].

4. Statistical Methods for Analyzing Industrial Structure and Efficiency

4.1. Descriptive Statistical Methods

Descriptive statistics form the foundation of analyzing industrial structures and efficiency by summarizing and visualizing data characteristics. Common descriptive indicators include measures of central tendency such as mean and median, measures of dispersion like variance and standard deviation, as well as frequency distributions. These methods provide initial insights into the distributional patterns, variability, and trends within industrial datasets. For example, summarizing firm sizes, output levels, or employment figures can help identify dominant sectors and structural changes over time [7].

4.2. Multivariate Statistical Analysis

To capture the complex relationships among multiple variables describing industrial characteristics, multivariate statistical methods are widely employed. Principal Component Analysis (PCA) reduces the dimensionality of data by transforming correlated variables into a smaller set of uncorrelated components, facilitating interpretation and visualization of industrial structure patterns. Cluster analysis groups firms or regions with similar industrial profiles, allowing for the identification of homogeneous groups and segmentation within the industry. These methods assist policymakers and researchers in uncovering latent structures and grouping units based on multidimensional attributes, which is essential for targeted industrial policy and efficiency improvement strategies.

4.3. Time Series and Panel Data Analysis

Given that industrial data often span multiple periods and entities, time series and panel data analyses are critical for examining dynamic changes and causal relationships. Time series analysis focuses on trends, cycles, and seasonality in industrial variables, enabling forecasting and the assessment of policy impacts over time. Panel data analysis, which combines cross-sectional and time series data, allows for controlling unobserved heterogeneity and enhancing estimation efficiency. Techniques such as fixed effects and random effects models enable researchers to investigate the influence of structural factors on industrial efficiency while accounting for both temporal and individual unit-specific variations [8].

4.4. Spatial Statistics and Geographically Weighted Regression

Spatial dependence and heterogeneity are important features in industrial economics, as firms and industries are geographically distributed with varying local characteristics. Spatial statistical methods, including spatial autocorrelation and spatial clustering, detect the presence of spatial patterns and interactions. Geographically Weighted Regression (GWR) extends traditional regression by allowing model parameters to vary spatially, capturing local variations in relationships between industrial variables and efficiency measures. This spatially explicit approach is particularly useful for regional policy analysis, enabling customized strategies that consider geographic diversity.

4.5. Current Applications of Statistical Models and Machine Learning

With the advent of big data and computational advancements, statistical modeling has increasingly integrated with machine learning techniques in industrial structure and efficiency analysis. Machine learning methods such as random forests, support vector machines, and neural networks provide powerful tools for classification, prediction, and pattern recognition in complex industrial datasets. These approaches complement traditional econometric models by handling nonlinearity, high dimensionality, and large-scale data more effectively [9]. Current research trends emphasize hybrid models combining econometric rigor with machine learning flexibility to improve efficiency measurement, structural analysis, and policy evaluation.

5. Empirical Studies and Applications

5.1. Review of Domestic and International Research on Industrial Structure and Efficiency

Empirical research on industrial structure and efficiency has been extensive both domestically and internationally, revealing important insights into economic development patterns and resource allocation. Internationally, studies have focused on advanced economies and emerging markets, analyzing how structural transformation impacts productivity growth and competitiveness. For example, investigations into manufacturing sectors in developed countries emphasize technology adoption and scale economies, while research in developing regions highlights structural shifts from agriculture to services. Domestic studies often concentrate on regional disparities and sectoral adjustments within the national economy, reflecting policy priorities and localized industrial policies. Collectively, these studies contribute to a nuanced understanding of how industrial structure evolution relates to efficiency improvements across different economic contexts.

5.2. Typical Case Analyses Across Industries and Regions

Case analyses of specific industries and regions offer valuable empirical evidence illustrating the heterogeneity of industrial efficiency. For instance, studies on high-technology manufacturing clusters reveal significant gains in scale efficiency and innovation-driven productivity, whereas traditional industries may face challenges related to overca-

capacity and technical inefficiency [10]. Regional case studies often highlight the role of geographic advantages, infrastructure, and institutional frameworks in shaping industrial performance. Differences between coastal and inland areas, urban and rural regions, or economically advanced and lagging zones demonstrate spatial disparities in efficiency and structural development. These typical cases underscore the importance of contextual factors in industrial economics research.

5.3. Data Sources and Data Processing Techniques

Reliable statistical data underpin empirical analysis of industrial structure and efficiency. Common data sources include national statistical bureaus, industry associations, firm-level surveys, and international databases such as the World Bank and OECD. Data processing techniques involve cleaning, normalization, and transformation to ensure consistency and comparability. Techniques such as handling missing data through imputation, outlier detection and treatment, and variable standardization are crucial for robust results. Advanced methods like panel data construction and spatial data integration enhance the richness and analytical power of empirical datasets. Proper data management is essential to address biases and measurement errors inherent in large-scale industrial data.

5.4. Challenges and Limitations in Empirical Research

Despite significant progress, empirical studies on industrial structure and efficiency face multiple challenges. Data limitations such as incomplete coverage, reporting errors, and low-frequency updates constrain analytical precision. Methodological issues include model specification errors, endogeneity, and difficulties in capturing dynamic and spatial interactions fully. Additionally, the heterogeneity of industries and regions complicates the generalization of findings. The rapid evolution of industrial sectors and external shocks, such as technological disruption and policy changes, also pose challenges for longitudinal studies. Addressing these limitations requires continuous methodological innovation, improved data collection practices, and integration of multidisciplinary approaches [11].

6. Discussion

6.1. Advantages and Limitations of Analyzing Industrial Structure and Efficiency from a Statistical Perspective

Analyzing industrial structure and efficiency through statistical methods offers distinct advantages. It enables the systematic quantification and visualization of complex economic phenomena, revealing underlying patterns and relationships that may not be apparent through qualitative analysis alone. Statistical techniques facilitate the integration of large-scale, multidimensional data, supporting robust and replicable findings. They also provide tools for hypothesis testing and model validation, enhancing the scientific rigor of industrial economics research. However, these approaches have limitations. Statistical models often rely on assumptions that may not fully capture economic realities, such as linearity or distributional homogeneity. Data quality and availability remain significant constraints, especially in emerging economies where comprehensive datasets are scarce. Moreover, purely statistical analyses may overlook contextual and institutional factors critical for interpreting industrial dynamics, necessitating complementary qualitative insights.

6.2. Future Research Trends and Prospects for Emerging Statistical Technologies

The future of industrial structure and efficiency research lies in the integration of advanced statistical and computational technologies. Emerging methodologies such as machine learning, artificial intelligence, and big data analytics promise to enhance the ac-

curacy and scope of efficiency measurement and industrial analysis [12]. These technologies can handle complex, nonlinear relationships and massive datasets, uncovering novel insights and predictive capabilities. Additionally, the increasing availability of high-frequency and spatially granular data facilitates dynamic and location-specific analyses. The integration of traditional econometric models with these new techniques is expected to yield hybrid approaches that combine interpretability with predictive power. Future research will likely focus on real-time monitoring, causal inference, and scenario simulation to better support policy-making in rapidly evolving industrial landscapes.

6.3. Policy Implications and Practical Applications

From a policy perspective, statistical analysis of industrial structure and efficiency provides valuable evidence to guide economic planning and industrial development strategies. It helps identify bottlenecks, resource misallocations, and regional disparities, enabling targeted interventions to enhance productivity and competitiveness. The insights gained support the design of tailored policies such as innovation incentives, infrastructure investment, and workforce development programs. Furthermore, real-time efficiency monitoring systems informed by advanced statistical models can assist policymakers in evaluating the impact of reforms and adjusting strategies promptly. In practice, firms and industry associations can utilize statistical findings to benchmark performance, optimize resource use, and foster innovation. Overall, the intersection of statistical analysis and industrial economics holds significant potential for driving sustainable economic growth.

7. Conclusion

This study provides a comprehensive examination of industrial structure and efficiency from a statistical perspective, highlighting several key findings. First, the multidimensional nature of economic efficiency — encompassing technical, allocative, and scale efficiency — was elucidated, along with rigorous methods such as Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) for measurement. Second, a range of statistical techniques including descriptive statistics, multivariate analysis, time series, panel data, and spatial methods were shown to be instrumental in capturing the complexity and dynamics of industrial structure and efficiency. Third, empirical evidence underscores the heterogeneity of industrial performance across regions and sectors, emphasizing the role of geographic, institutional, and technological factors.

The significance of this research lies in its integrative approach, bridging traditional economic theory with modern statistical and machine learning methods to enhance the precision and depth of industrial analysis. By synthesizing methodological advances and empirical applications, the study contributes to a more nuanced understanding of industrial efficiency and structural evolution. It also offers a foundation for more informed policymaking and strategic decision-making in industrial development.

Looking forward, future research should continue to explore the integration of emerging data sources and advanced analytical techniques, such as artificial intelligence and big data analytics, to address current limitations related to data quality, model assumptions, and dynamic complexity. Emphasis on spatial-temporal modeling and causal inference will be particularly valuable. Moreover, interdisciplinary approaches combining economics, statistics, and computational science hold promise for uncovering new insights into industrial transformation processes. Such efforts will ultimately support sustainable economic growth and industrial competitiveness in an increasingly complex global environment.

References

1. M. Koengkan, J. A. Fuinhas, E. Kazemzadeh, F. Osmani, N. K. Alavijeh, A. Auza, and M. Teixeira, "Measuring the economic efficiency performance in Latin American and Caribbean countries: An empirical evidence from stochastic production frontier and data envelopment analysis," *Int. Econ.*, vol. 169, pp. 43–54, 2022, doi: 10.1016/j.inteco.2021.11.004.

2. N. A. Bhat and S. Kaur, "Technical efficiency analysis of Indian IT industry: A panel data stochastic frontier approach," *Millenn. Asia*, vol. 15, no. 2, pp. 327–348, 2024, doi: 10.1177/09763996221082199.
3. L. T. Nguyen, S. Ratnasiri, and L. Wagner, "Industrial energy efficiency and determinants in Vietnam: A stochastic frontier analysis using firm-level data," *Appl. Econ.*, vol. 56, no. 14, pp. 1636–1651, 2024, doi: 10.1080/00036846.2023.2177592.
4. C. Zhang and P. Chen, "Industrialization, urbanization, and carbon emission efficiency of Yangtze River Economic Belt—empirical analysis based on stochastic frontier model," *Environ. Sci. Pollut. Res.*, vol. 28, no. 47, pp. 66914–66929, 2021, doi: 10.1007/s11356-021-15309-z.
5. M. C. D'Errico, "Sustainable economic growth and energy security nexus: A stochastic frontier analysis across OECD countries," *Energy Econ.*, vol. 132, p. 107447, 2024, doi: 10.1016/j.eneco.2024.107447.
6. M. Wang, Y. Wu, X. Zhang, and L. Lei, "How does industrial agglomeration affect internal structures of green economy in China? An analysis based on a three-hierarchy meta-frontier DEA and systematic GMM approach," *Technol. Forecast. Soc. Change*, vol. 206, p. 123560, 2024, doi: 10.1016/j.techfore.2024.123560.
7. Z. Geng, G. Song, Y. Han, and C. Chu, "Static and dynamic energy structure analysis in the world for resource optimization using total factor productivity method based on slacks-based measure integrating data envelopment analysis," *Energy Convers. Manage.*, vol. 228, p. 113713, 2021, doi: 10.1016/j.enconman.2020.113713.
8. T. Wang, K. Sun, and S. Kumbhakar, "A new semiparametric stochastic frontier model: addressing inefficiency and model flexibility using panel data," *Empir. Econ.*, pp. 1–38, 2025, doi: 10.1007/s00181-024-02708-7.
9. J. Barrera-Santana, G. A. Marrero, and F. J. Ramos-Real, "Energy efficiency and energy governance: A stochastic frontier analysis approach," *Energy J.*, vol. 43, no. 6, pp. 243–284, 2022, doi: 10.5547/01956574.43.6.jbar.
10. A. E. Ripoll-Zarraga, J. L. F. Miguel, and C. F. Belda, "Visualisation of Data Envelopment Analysis in primary health services," *Health Care Manag. Sci.*, pp. 1–27, 2025, doi: 10.1007/s10729-025-09702-0.
11. J. Zhou and M. Shao, "Evaluation of green innovation efficiency in Chinese provincial regions under high-quality development and its influencing factors: An empirical study based on hybrid data envelopment analysis and multilevel mixed-effects Tobit models," *Sustainability*, vol. 15, no. 14, p. 11079, 2023, doi: 10.3390/su151411079.
12. N. Arora, D. Sharma, and S. J. Talwar, "A sustainable measure of efficiency performance and validity of Environmental Kuznets Curve—an intercountry Data Envelopment Analysis approach," *J. Econ. Adm. Sci.*, 2025, doi: 10.1108/JEAS-07-2024-0256.

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