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A Decision-Making Model for Supplier Selection Based on Data Envelopment Analysis

H. Moradi[1,*], M. Abbaszadeh[2]

Efficiency is a crucial economic factor for companies, as it directly impacts costs and resource utilization. The main objective of this study is to assess the technical and scale efficiency of 15 suppliers of a production unit over a three year (2020-2022) using data envelopment analysis (DEA). This analysis will be conducted under two assumptions - constant returns to scale and variable returns to scale. Efficiency plays a pivotal role in impacting costs and optimizing resource utilization for businesses. This study aims to evaluate the technical and scale efficiency of 15 suppliers within a production unit over a three-year period (2020-2022) using data envelopment analysis (DEA). The analysis will involve assessing efficiency under two assumptions - constant returns to scale and variable returns to scale. Variables were selected based on indicator availability, representation principles, and expert input, with inputs including investment, non-operating expense costs, and operational expenses (comprising raw material costs, wages, and overheads), while outputs encompass net sales and return on investment. Results from the study indicated that supplier one, scoring 0.5716 assuming constant returns to scale and 0.6790 under variable returns to scale, emerged as the least efficient supplier. Interestingly, only two suppliers (8 and 15) demonstrated higher efficiency levels. However, the net technical efficiency of the supply chain showed an increasing concentration, which indicates the overall reduction of the gap between suppliers and the improvement of the net technical efficiency in the supply chain of the production unit. This study provides valuable insights into the differences between suppliers from a macro perspective and offers guidance for manufacturing units looking to expand their supply chain.

Keywords*: Data Envelopment Analysis, Supply Chain, Scale efficiency, Technical efficiency.*

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1. Introduction

In the dynamic landscape of modern business, organizations are faced with increasingly intricate decisions when it comes to selecting suppliers (Hosseini Dolatabad et al. [6]). This critical choice directly impacts an organization's ability to deliver high-quality products and services efficiently (Salhab et al. [20]). Despite the plethora of suppliers available, finding the right supplier has become a challenging issue in organizations (Echefaj et al. [3]). Thus, organizations have taken strict measures to select suppliers to ensure that they comply with the organization's supply chain considerations (Moradi et al.[12]). The selection of a suitable supplier holds sway over cost management, quality assurance, on-time delivery, supply chain responsiveness, and innovation capabilities (Sharma and Joshi, [22]). Conversely, opting for an unsuitable supplier can result in heightened costs, product defects, delays, and disruptions in the supply chain (Kanike 2023). Therefore, evaluating supplier

[1] Department of Management, Yazd Branch, Islamic Azad University, Yazd, Iran, Email: h.moradi@iauyazd.ac.ir.
[2] Department of Management, Yazd Branch, Islamic Azad University, Yazd, Iran, Email: m.abbaszadeh98@gmail.com.

performance is paramount to mitigate risks and uphold the seamless operation of the supply chain (Tong, Wang, and Pu, [26]). To tackle this challenge effectively, organizations have turned to data-driven approaches to inform their decision-making processes (Teng, Zhang, and Sun,[25]). These methodologies empower decision-makers to make objective, data-backed decisions rather than relying on subjective judgments or personal biases. For this purpose, various methods have been introduced for such evaluation, including DEA. These methods enable organizations to analyze and compare the efficiency of suppliers by considering several inputs and outputs simultaneously and provide a comprehensive evaluation framework (Moradi and Meybodi, [23]) . Classical models of the DEA method are divided into two categories: CCR and BCC (Hosseinzadeh Lotfi et al. [7]), each offering perspectives on inputs and outputs. The CCR model operates under the constant returns to scale (CRS) assumption, while the BCC model operates under the variable returns to scale (VRS) assumption (Babaei-Meybodi, Moradi, and Abbaszadeh, [1]) .

This study endeavors to equip decision-makers with the requisite tools to streamline the supplier selection process and make data-informed choices. By utilizing this decision-making framework, organizations can enhance their competitive edge, mitigate supply chain vulnerabilities, and cultivate enduring partnerships with suppliers that align with their strategic objectives. In this regard, by providing an appropriate model and using the available information, the technical efficiency of the suppliers is calculated in two scale assumptions, CRS and VRS, Then, considering that managers are interested in obtaining scale effects, scale efficiency and the kinds of return to scale of suppliers are determined. Furthermore, the study offers strategies to guide inefficient suppliers toward the efficiency frontier. In the next section, we provide a brief overview of the theoretical framework of the research, describe the data used, calculate the efficiency values, discuss the findings, and draw relevant conclusions.

2. The theoretical framework of research

In this section, we will provide an overview of the research methods employed in this study, drawing upon relevant literature. Additionally, we will discuss the background of the research and outline the specific research gap that this study aims to address.

2.1. Supply chain management

In general, supply chain management enables the timely movement of goods from suppliers to manufacturers and from manufacturers to customers. Ultimately, this enables the organization to keep costs low (Seuring et al. [21]). Four decades have passed since the presentation of this concept by Oliver and Weber, and many advances have been made in the analysis, investigation, and development of concepts related to it (Oliver and Webber, [16]). In today's competitive business environment, organizations are increasingly focusing on their supply chain as it has become a crucial aspect that can differentiate them from their competitors and improve their position in the global market (Rezapour, Farahani, and Pourakbar, [18]). In other words, supply chain management is no longer a cost center (Chanchaichujit, Balasubramanian, and Charmaine, [2]); rather, it is one of the components of competitive strategies for the productivity and profitability of an organization (Marzband, [10]). In recent years, supply chain evaluation has been the subject of many researchers who have proposed and used different methods for this purpose. For example, Mzougui et al. used conventional multi-criteria decision-making (MCDM) methods to evaluate and select suppliers (Mzougui et al. [15]). Some researchers, such as Moradi et al., use the DEA method alone (Moradi et al. [13]), and others have used a combination of DEA with MCDM (Moradi et al. [14]). In this study, classic DEA models were used to evaluate supply chains.

2.2. Data envelopment analysis

Data envelopment analysis is a linear programming technique used in this study to evaluate the efficiency of suppliers in a production unit. This method has been used for many years across diverse fields (Sharma and Sharma,[23]). Efficiency values resulting from the implementation of DEA are confined between zero and one. Suppliers are considered efficient if they obtain an efficiency score of one, implying that it is not possible to increase or decrease the outputs or inputs (Saavedra-Nieves and Fiestras-Janeiro, [19]). Suppliers with efficiency values less than one are deemed ineffective (Shetty and Pakkala, [24]). Each supplier is evaluated by comparing its efficiency with the efficiency limit (Moradi et al. [13]). The efficiency frontier is composed of the best-performing suppliers (Veiga, Pinheiro de Lima, and Gouvea da Costa, [27]). If a supplier lies on the efficiency frontier, it is considered fully efficient; otherwise, it is considered inefficient. The shape of the frontier is determined partially by assuming either CRS or VRS. The VRS model establishes a boundary by utilizing a convex body, restricting the efficiency of the CRS model (Podinovski, [17]). In this study, CRS and VRS efficiency values were calculated to compare the efficiency of the scale. Considering that these two models are presented in two orientations, input-oriented and output-oriented, the nature of the model needs to be determined first. Input-oriented models aim to minimize inputs while keeping the output level constant, whereas output-oriented models strive to increase the output level while keeping inputs constant (Hosseinzadeh Lotfi et al. [7]). In this study, managers have more control over inputs than outputs. Therefore, an input-oriented nature was chosen, reflecting the primary goals of policymakers, such as cost reduction and resource limitation based on accountability. Equations 1 and 2 illustrate the input-oriented CCR and BCC models, respectively.

Input-oriented CCR model

$$
\begin{aligned}
&\text{Min } Z_0 = \theta \\
&\text{st}: \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad (r = 1,2,\ldots,s) \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0} \quad (i = 1,2,\ldots,m) \\
&\qquad \lambda_j \geq 0
\end{aligned}
\tag{1}
$$

Input-oriented BCC model

$$
\begin{aligned}
&\text{Min } Z_0 = \theta \\
&\text{st}: \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} \quad (r = 1,2,\ldots,s) \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{i0} \quad (i = 1,2,\ldots,m) \\
&\qquad \sum\nolimits_{j=1}^{n} \lambda_j = 1 \qquad (j = 1,2,\ldots,n) \\
&\qquad \lambda_j \geq 0 \;\; , \;\; \theta \text{ is free}
\end{aligned}
\tag{2}
$$

This study considers determining the efficiency value of suppliers at their optimal scale, known as scale efficiency. The efficiency values obtained by assuming a constant return to scale model (Relation 1) are not net and are associated with scale efficiency. Therefore, to separate technical efficiency from scale efficiency, the VRS model was used to measure net technical efficiency. As is clear from relations 1 and 2, the VRS pattern is obtained by adding an adverb to the CRS pattern. If there is a discrepancy in the efficiency values derived from the VRS and CRS models, it suggests the presence of scale inefficiency. The scale inefficiency can be calculated as the difference between the technical efficiency of the VRS and CRS models. Therefore, according to the said content, we have:

CRS Score = net technical Eff (VRS Score) × Scale Eff (3)

Therefore:

Scale Eff = CRS Score/ VRS Score (4)

The values of scale efficiency (Relation 4) help to understand the extent of the difference between suppliers since some suppliers do not operate under optimal conditions.

2.3. Research Background

Considerable research has been dedicated to measuring technical efficiency, along with its scale, advantages, and benefits. Table 1 lists several studies closely related to the subject matter of the current research.

Table 1. Research Background

Researcher	Title	Description	Result
(Garcia Sanchez,[4])	Technical and scale efficiency in Spanish urban transport: Estimating with data envelopment analysis	This study investigated the technical and scale efficiency of the Spanish transportation system using DEA	The results showed that the average technical efficiency and the scale of the Spanish public transportation system are 94.91 and 52.02%, respectively, and increasing service access is very important as a quality parameter in its performance
(Sharma and Sharma,[23])	Analyzing the technical and scale efficiency Of small industries in India: state-wise cluster study	This study examined the technical and scale efficiencies of 23 Indian states. To do this, he used the DEA model, specifically the BCC.	The results showed that seven states were technically efficient, whereas only two states were efficient in terms of scale efficiency. Most states operate with diminishing returns to scale, indicating more investment and employment creation spaces.
(Kirigia and Asbu, [9])	Technical and scale efficiency of public community hospitals in Eritrea: an exploratory study	This study investigated the efficiency of Eritrean hospitals using a two-stage DEA to estimate the relative technical efficiency and scale of public hospitals.	This study showed that hospital data collected routinely in Eritrea can be used to identify relatively inefficient hospitals, as well as the sources of their inefficiency.
(Wanke and Barros, [28])	Public-Private Partnerships and Scale Efficiency in Brazilian Ports: Evidence from Two-Stage DEA Analysis	This study evaluates the impact of public and private partnerships of public ports in Brazil using the DEA method. This study aimed to achieve higher levels of scale efficiency.	The results indicated a strong positive impact of public-private partnerships on port-scale efficiency, corroborating their impacts on the most productive scale size.
(Havidz et al. [5])	Technical and Scale Efficiency Employing Data Envelopment Analysis: Empirical Evidence from	This research investigated the technical efficiency and scale of 10 public Islamic banks in Indonesia with the intermediation approach and through the DEA method	The results showed that the average technical efficiency in the whole quarter for all Islamic state banks is 72.9% and the technical inefficiency is caused by net technical inefficiency, compared to scale inefficiency
(Yousef, Al-Salih, and Obaid [29])	Measuring the Relative Efficiency and Scale Efficiency of Health Organization in Thi Qar Province Using BCC Model	This study measured the relative and scale efficiencies of the health centers of Thi Qar province, Iraq, using the BCC model.	The results indicated that out of the eight treatment centers under investigation, six centers were efficient. In addition, the analysis of scale efficiency values showed that most hospitals achieved high efficiency in 2020 and improved their performance by 2021.

2.4. Research gap

Efficiency evaluation in the supply chain has garnered significant attention in academic research. Prior studies have explored various approaches to measure technical efficiency and scale efficiency within the context of supply chains. However, when it comes to production units, particularly considering the dynamics of time, there is a notable lack of comprehensive research. Addressing these gaps and providing a systematic approach to evaluating supply chain scale and technical efficiency, this research not only enhances the current understanding of efficiency evaluation but also paves the way for future research in this field.

3. Research methodology

The statistical population for this study consists of 15 suppliers from a production unit that were active during the period from 2020 to 2022. Before measuring the efficiency of these suppliers, it is essential to determine the specific input and output variables that will be considered in the analysis. In selecting these variables, the study follows the principles of representation and availability of indicators, taking into account expert opinions and similar research in the field. For the purposes of this study, the chosen input variables include investment, nonoperating expense cost, and various operating costs such as raw material costs, wages, and overhead costs. These inputs provide insights into the resources and expenditures required for supplier performance. On the other hand, the selected output variables are net sales and return on investment (ROI). Net sales reflect the revenue generated by the supplier, while ROI measures the profitability and efficiency of the supplier's investment. To calculate the efficiency of the suppliers, an appropriate DEA model is chosen based on the nature of the system and the selected variables. In this study, a single-stage BCC and CCR input-oriented DEA model is utilized (as indicated in Relations 1 to 2). Additionally, scale efficiency (Relation 4) is incorporated to further understand the differences in supplier performance and identify those who are not operating under optimal conditions. The collected data are analyzed using software such as GAMS, EXCEL, and SPSS. These tools facilitate the computation and aggregation of the efficiency values based on the chosen DEA model, allowing for robust analysis and interpretation of the results. The process of single-stage DEA in the study is illustrated in Figure 1.

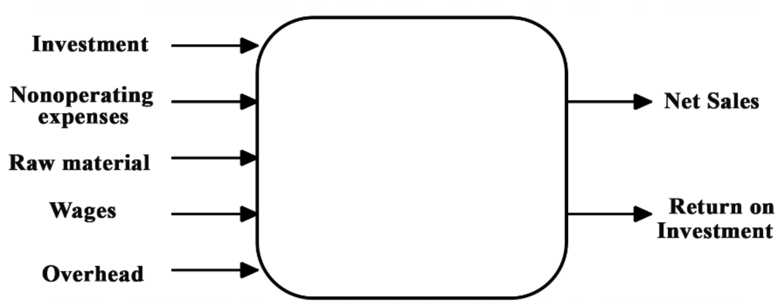


Figure 1. one-stage DEA process

4. Findings

First, descriptive statistics was used to organize and describe the data used in this study. The indicators used for the descriptive analysis included the mean, maximum, minimum, and standard deviation. Table 2 lists the data.

Table 2. Descriptive analysis of research data

	Mean	Std. Deviation	Minimum	Maximum
ROI	10. 18	1. 600	7	14
Net sales	792391. 84	371308. 610	108738	2079720
Nonoperating expenses	105014. 40	79416. 550	50876	375786
Overhead costs	240407. 64	97666. 632	80874	528158
Wages Cost	43210. 20	8374. 129	30387	60434
Raw material costs	212. 87	284. 512	52	984
Investment	406688. 89	198919. 790	87000	1020000

As mentioned, after collecting information on the suppliers of the system under review from 2020 to 2022, the efficiency of the suppliers was calculated using the GAMS software. The efficiency results for the suppliers during the period under review are shown in Table 3. Equation 4 was used to calculate the efficiency of the scale, and the efficiency values of the scale were calculated using Equation 4. Subsequently, the efficiency values obtained from the implementation of BCC and CC are compared. If these two values are equal, the type of return to scale is constant (CRS), and otherwise, it is variable .

If a variable return to scale was identified, efficiency values were calculated using the BCC model with decreasing returns to scale. Subsequently, the results of this approach and the BCC model were compared to determine the type of return to scale. If these two values are equal, it implies a decreasing return to scale (DRS). However, if the values are not equal, this suggests an increasing return to scale (IRS).

Table 3. supplier efficiency values during the period 2020-2021

DMU's	Year	CRS	VRS	Scale Eff	kinds of returns to scale
DMU1	1399	0.5726	0.7376	0.7763	DRS
	1400	0.6243	0.6484	0.9629	DRS
	1401	0.518	0.6511	0.7955	IRS
		0.5716	0.6790	0.8449	
DMU2	1399	0.7615	1	0.7615	DRS
	1400	0.924	1	0.924	DRS
	1401	0.8403	0.9259	0.9075	DRS
		0.8419	0.9753	0.8643	
DMU3	1399	0.8154	0.8247	0.9887	DRS
	1400	0.6592	0.8464	0.7788	DRS
	1401	0.6658	0.7839	0.8493	DRS

		0.7135	0.8183	0.8723	
DMU4	1399	0.921	0.93	0.9904	DRS
	1400	1	1	1	CRS
	1401	0.9145	0.9456	0.9671	IRS
		0.9452	0.9585	0.9858	
DMU5	1399	0.8809	0.9202	0.9573	IRS
	1400	0.9493	0.9498	0.9994	DRS
	1401	0.8837	0.9107	0.9707	IRS
		0.9046	0.9269	0.9758	
DMU6	1399	1	1	1	IRS
	1400	0.9111	1	0.9111	CRS
	1401	0.9631	1	0.9631	IRS
		0.9581	1.0000	0.9581	
DMU7	1399	0.8615	0.9859	0.8738	IRS
	1400	0.7871	0.8601	0.9151	DRS
	1401	1	1	0.9285	IRS
		0.8829	0.9487	0.9058	
DMU8	1399	1	1	1	CRS
	1400	1	1	1	CRS
	1401	1	1	1	CRS
		1.0000	1.0000	1.0000	
DMU9	1399	0.888	1	0.888	IRS
	1400	0.9306	1	0.9306	IRS
	1401	1	1	1	CRS
		0.9395	1.0000	0.9395	
DMU10	1399	0.8488	0.8563	0.9912	DRS
	1400	0.8612	1	0.8612	IRS
	1401	0.9507	1	0.9507	IRS
		0.8869	0.9521	0.9344	
DMU11	1399	0.7763	0.7765	0.9998	IRS
	1400	0.6866	0.7244	0.9479	IRS
	1401	0.675	0.6783	0.9952	DRS
		0.7126	0.7264	0.9810	
DMU12	1399	0.8321	0.8402	0.9904	DRS
	1400	0.7298	0.7985	0.9139	DRS
	1401	0.7183	0.7771	0.9243	DRS
		0.7601	0.8053	0.9429	
DMU13	1399	0.9126	0.9183	0.9938	DRS
	1400	0.8862	0.9429	0.9399	DRS
	1401	0.9935	1	0.9935	IRS

		0.9308	0.9537	0.9757	
DMU14	1399	0.8916	0.8987	0.9921	IRS
	1400	0.7881	1	1	IRS
	1401	0.8163	1	0.8163	IRS
		0.8320	0.9662	0.9361	
DMU15	1399	1	1	1	CRS
	1400	1	1	1	CRS
	1401	1	1	1	CRS
		1.0000	1.0000	1.0000	
Average		0.8586	0.9140		

In Table 3, the efficiencies of the CCR and BCC represent the existing and optimal conditions, respectively, and the scale efficiency is obtained using Equation 4. These are long-term conceptual values that indicate the ratio of an increase in output to an increase in the number of inputs. In addition, the average net technical efficiency of the suppliers from 2020 to 2022 was calculated. As shown in Figure 2, the average net technical efficiency of the eight suppliers is 0. 95 to 1, among these three suppliers, 8, 9, and 15 obtain the maximum efficiency. The average net technical efficiency of the two suppliers was 1, followed by 11, with the lowest average technical efficiency among the 15 suppliers.

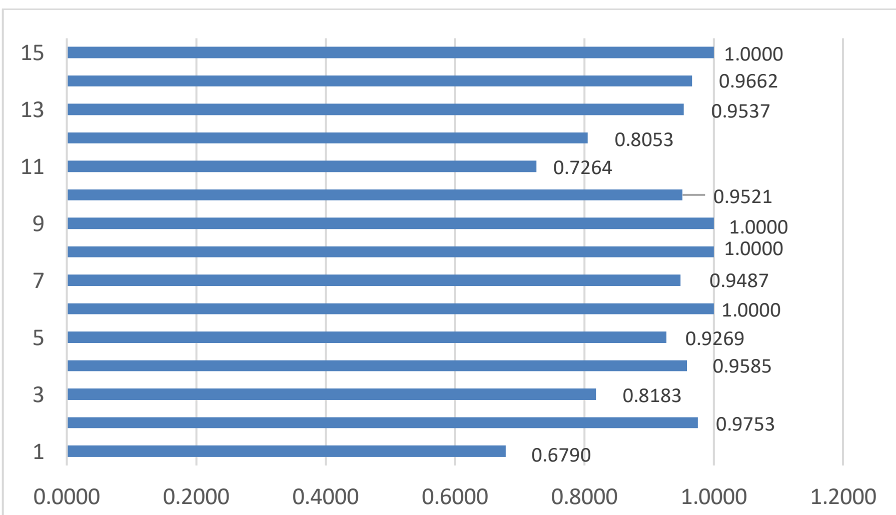


Figure 2. Average net technical efficiency

In addition, the average efficiency of the scale of suppliers from 2020 to 2022 was calculated. As shown in Figure 3, the average scale efficiency of seven suppliers is in the range of 0.95 to 1, among which two suppliers, 8 and 15, have obtained the maximum efficiency. The average net technical efficiency of two suppliers 1 and then 11 has the lowest average technical efficiency among 15 suppliers.

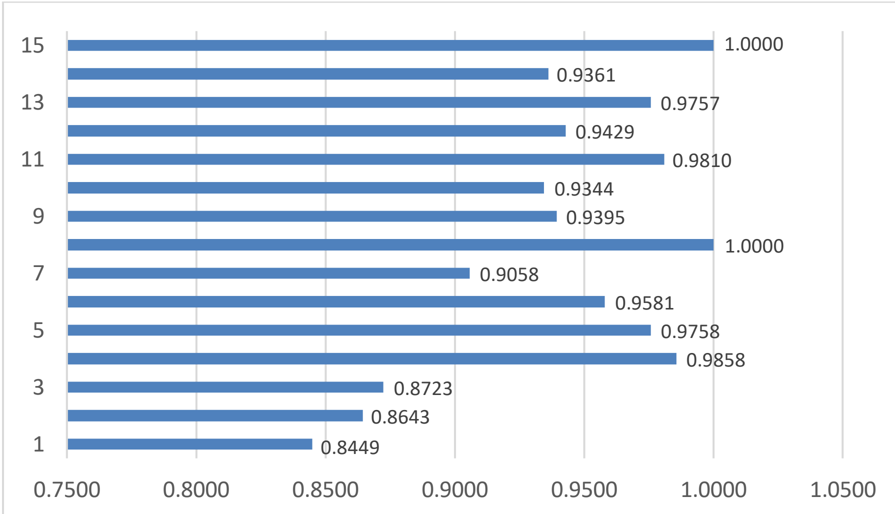
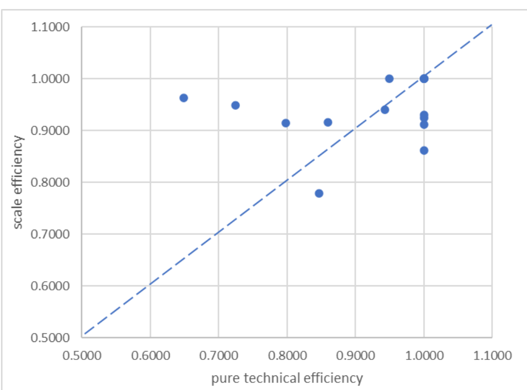
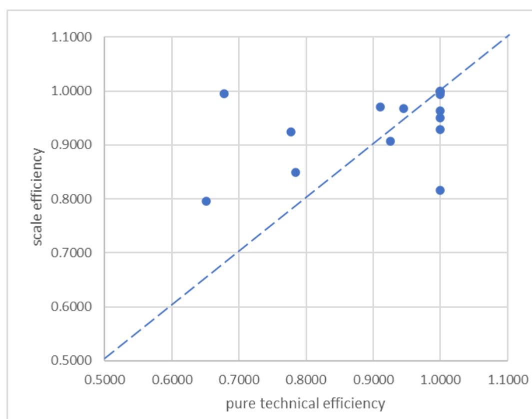


Fig. 3. Average scale efficiency

Figure 4 (a, b) shows the net technical efficiency and scale efficiency relationship for 2020 and 2022, respectively. In these graphs, the x-axis shows net technical efficiency, and the y-axis shows scale efficiency. Scattered points below the 45-degree line show that are the contribution of net technical efficiency in the calculation of efficiency greater than the scale efficiency. Specifically, the scattered points above the 45° line show that the contribution of scale efficiency to the calculation of efficiency is greater than that of net technical efficiency.



a. The year 2020



b. The year 2022

Figure 4. Scatter diagram of net technical, and scale efficiencies

In general, the efficiency distribution of the scale of the supply chain of the production unit under investigation from 2020 to 2022 is increasingly scattered, while the distribution of net technical efficiency is increasingly concentrated in the same period. The increasingly concentrated distribution of net technical efficiency shows that the gap between suppliers is decreasing and reflects, to some extent, the progress of net technical efficiency in the supply chain of the manufacturing unit under consideration.

5. Discussion

This study undertakes an input-oriented approach to calculate the efficiency values of suppliers within a production unit. The findings showcase the effectiveness of considering inputs such as investment, non-operating expense costs, and various operating costs (e.g., raw material costs, wages, and overhead costs), along with outputs like net sales and return on investment, to create a comprehensive measure of efficiency. The results emphasize the need for integrated strategies in supply chain management. In addition, with some adjustments to the analysis intervals, this method for supply chain analysis can help managers adjust their supply chain strategies more easily, especially when they feel that the chain is exposed to risks. Examining the technical efficiency values under both constant and variable scale efficiency reveals key insights. The technical efficiency values in the case of variable scale efficiency are higher compared to those under constant scale efficiency due to the production function in the VRS mode is Always under the CRS function. The efficiency value of suppliers under constant returns to scale is determined to be 0.8586, while under variable returns to scale, it is 0.9140. These values indicate that suppliers should increase their output by approximately 1.06 times to achieve efficiency and by around 1.09 times to attain optimal scale while maintaining efficiency. Analyzing the average efficiency across the supplier periods identifies supplier 1 as the inefficient supplier with scores of 0.5716 (constant returns to scale) and 0.6790 (variable returns to scale). Alternatively, suppliers 8 and 15 demonstrate the highest efficiency levels, operating optimally at an efficient scale. This study's quantification of efficiency values under different scale assumptions enables the identification of efficient suppliers that can serve as benchmarks for others. Suppliers 1, 4, and 13 in the third period; suppliers 5, 6, and 7 in the first and third periods; suppliers 9 and 11 in the first and second periods; supplier 10 in the second and third periods; supplier 13 in the third period; and supplier 14 in all three periods have returned to the ascending scale. Thus, these suppliers had the necessary economic justification for their activities during the aforementioned periods. According to the principles of microeconomics, in this case, the curves of final and average production have an upward trend. As a result, the economic unit is not operating at an optimal level of production and is in the initial phase of production. This means that the curves of marginal and average costs have a downward trend, and the supplier is in the downward part of the LAC. This demonstrates the economies of scale, particularly for supplier 14. The highest efficiency method for the scale related to supplier 11 was 0.9858. The implication is that the efficiency of this supplier, in terms of both constant and variable returns to scale, is almost the same. Therefore, this supplier operates near the second production area and still has the economic justification to expand its activity. Supplier 2 also has a decreasing return to scale, which indicates a lack of economies of scale; in other words, this supplier is in the ascending part of the LAC. The findings also highlight the need for attention to suppliers with decreasing returns to scale, such as supplier 2, which indicates a lack of economies of scale; in other words, this supplier is in the ascending part of the LAC. Efficient suppliers with decreasing returns, such as supplier 2, will lose their efficiency compared to other suppliers if the use of inputs increases without changing other conditions. As a result of the development and expansion of production in this group of suppliers, the policy will not be efficient only with the expansion of inputs. However, this problem is different for efficient suppliers with increasing returns to scale. By developing and expanding their production using other inputs, these suppliers can positively impact their technical efficiency if the conditions of the other suppliers are constant. This situation is especially true for supplier 6 in the third period. However, suppliers with constant returns to scale can increase production by using more inputs while maintaining existing technical efficiency.

While the implementation of our method has yielded significant implications, future research can further improve and extend the application of this systematic framework. In particular, there is a need to expand the scope of our integrated framework to different regions and sectors, enabling comprehensive comparisons and benchmarking on a larger scale. Additionally, future research can focus on incorporating multi-step production processes when calculating comprehensive efficiency values. This would provide a more accurate assessment of supplier performance, considering the complexities of multi-stage manufacturing processes. Moreover, it is recommended to utilize the Malmquist index to examine the changes in total productivity during the study period and evaluate the trend of changes in suppliers' productivity. While our study primarily focuses on quantitative data analysis, future research could explore the integration of qualitative factors. Incorporating these qualitative dimensions could offer a more holistic assessment of supplier performance and aid in making more informed decisions.

Limitation

While this research did not encounter serious limitations, a few aspects warrant consideration:

1. Data Limitations: The study relied on historical data spanning from 2020 to 2022. Given the rapid evolution of the business landscape, utilizing dated data may not entirely capture current dynamics and challenges.

2. Scope of Inputs and Outputs: The study focused on a specific set of inputs and outputs to assess supplier performance. Expanding the scope to encompass additional performance measures or considering different combinations of inputs and outputs would offer a more comprehensive understanding of supplier performance and efficiency.

Conflict of Interest Statement

We confirm that all listed authors have thoroughly reviewed and approved the manuscript and have no conflicts of interest pertaining to this work. Additionally, the authors have collectively endorsed the order in which they are listed in the manuscript.

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