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A DEA-TOBIT ANALYSIS ON THE OPERATIONAL EFFICIENCY OF LOGISTICS FIRMS IN TÜRKİYE

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Abstract

Performance evaluation research on logistics firms mainly concentrates on financial performance. Therefore, there is a need for further research on operational efficiency, which constitutes an essential component of performance evaluation. On these grounds, the purpose of this paper is to analyze the operational efficiency of selected logistics firms from Borsa Istanbul (BIST) Transportation Index in Türkiye and to evaluate the influential factors of efficiency. In this way, this research aims to contribute to the literature by incorporating operational input/output factors and assessing the causal factors that determine efficiency in logistics firms. The sample consists of six companies selected, and the period of analysis spans from 2019 to 2024. Methodologically, a two-phase investigation is applied with an integrated two-stage DEA and Tobit analysis approach. The findings indicate that efficiency scores vary across firms, with only a single firm consistently operating at the efficient frontier throughout the period under evaluation. Besides, slack-based analysis points to the need for efficiency improvements, especially in operations and inventory management areas. The results of the Tobit analysis emphasize the importance of working capital, which is vital for daily operations, and staff, which is essential for the operational efficiency of logistics companies that rely heavily on labor. Moreover, the analysis suggests that logistics firms should maintain their flexibility early on and avoid organizational rigidity for better operational performance, as they gain more experience in the sector.

Keywords: International Logistics, Operational Efficiency, Data Envelopment Analysis, Tobit Analysis, Performance Measurement

JEL Codes: L91, M20, M21

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INTRODUCTION

Today's global business environment forces all businesses, in service or manufacturing sector, to increase their operational efficiency. In this setting, the logistics business stands as a prominent sector that supports other industries, particularly the manufacturing industry (Wang & Zhou, 2021). In the current integrated supply chain landscape, transport and logistics operations, which are outsourced from logistics companies, have become the main drivers of performance in the manufacturing sector (Smirnova et al., 2024). The logistics sector has substantial potential for creating jobs, increasing productivity across integrated sectors, and boosting industrial and service output. However, all of these potential contributions depend on its performance. With the global integration of supply chains, many customers expect high-quality services at competitive prices from logistics companies. As open markets become more penetrated, competition intensifies for logistics companies, particularly in emerging markets, with the entry of global operators. Hence, assessing efficiency in this industry has become a significant research topic, particularly in a developing market context (Qin & Wu, 2012). As a developing country, Türkiye is at the center of international trade due to its economic growth and strategic geographic location that connects Asia and Europe. The logistics sector in Türkiye employed over 1.7 million people in 2023 (Turkstat, 2025) and had a market size of $100 billion, ranking 11th in the world (Ministry of Trade, 2025). With a growing focus on the Middle Corridor as an alternative route amid recent geopolitical tensions, Türkiye has strengthened its position as a key logistics hub within global supply chains. This creates significant opportunities for market growth for logistics companies in Türkiye. However, taking advantage of these opportunities depends on the operational efficiency of the companies, especially given the rapidly changing and fast-paced nature of the logistics sector (Sarkar et al., 2025). Hence, examination of the operational performance of this sector is becoming more crucial. In this context, this paper focuses on the operational efficiency of logistics companies in Türkiye, as a relevant and timely topic from an emerging market setting.

Regarding the scope of operational efficiency, productivity increase can be achieved through continuous improvement of business processes, which involves an overall performance improvement framework. This includes optimizing resources and cutting costs while preserving or enhancing productivity, which is primarily determined by an organization's internal resources (Handoyo et al., 2023). So, focusing on the operational area and explaining the performance of logistics firms from a supply chain view would reveal important managerial implications for industry practitioners by identifying the most relevant functions and pinpointing areas that require improvement. However, previous research has extensively concentrated on the financial performance of logistics companies in Türkiye (see, for instance, Aksungur & Deran, 2021; Alnıpak & Kale, 2021; İyigün, 2024), where the assessment of operational efficiency remains an understudied topic. Moreover, these studies predominantly use financial ratios in

performance analysis as a result of the main research stream seeking implications in the financial area. Additionally, there is a knowledge gap regarding the firm characteristics that impact the operational performance of logistics companies, underscoring the need for further research to expand the managerial insights. Given this background, the purpose of this study is to fill these research gaps by analyzing the performance of logistics companies in Türkiye in terms of operational parameters and identifying firm characteristics that influence efficiency, with a focus on operational performance.

Conceptually, Karlaftis & Tsamboulas (2012) define efficiency as the comparison between the amount of input and the corresponding output bundles with the optimal input and output bundle used in a production process. Efficiency can be measured through two main approaches: technical efficiency and allocative efficiency. Technical efficiency measures a decision-making unit (DMU)'s success in maximizing the utilization of its production factors to their fullest potential. On the other hand, allocative efficiency refers to DMU's ability to select an input combination that produces a specified amount of output at the minimum cost. While technical efficiency concerns itself with quantity, allocative efficiency focuses on price (Barros & José Mascarenhas, 2005). Based on these brief descriptions, the focus of this paper is technical efficiency. In terms of techniques, the Stochastic Frontier Approach (SFA) and Data Envelopment Analysis (DEA) are two widely used parametric and non-parametric frontier techniques, respectively, where efficiency scores are determined based on a production function derived from the system. In parametric methods, the production frontier form is established a priori, imposing further assumptions about the efficiency distribution, while non-parametric methods do not require such assumptions (Kersten, 1996). Hence, the current study employs DEA technique which is a non-parametric method offering more flexibility in efficiency analysis. In the next phase of this study, Tobit analysis is used to identify the firm characteristics that affect operational efficiency. In this final analysis, the efficiency scores from the DEA analysis, which serve as dependent variables, are regressed on the potential influential factors that were selected based on the literature. Since the efficiency scores are bounded (censored) at the maximum efficiency score, Tobit model is the appropriate method, as it is designed to estimate the relationship between variables when the dependent variable is censored.

The rest of the paper is organized as follows. In the next section, existing research examining the performance of logistics firms, largely in Türkiye, is discussed. Following that, two-stage DEA approach and Tobit model are explained as the two-phase research techniques of this paper. After that, the results of the performance assessment, slack-based analysis and Tobit analysis are provided, and the findings are discussed. Finally, concluding remarks and practical implications are drawn.

LITERATURE ON THE PERFORMANCE ASSESSMENT OF LOGISTICS COMPANIES

The focus of this study is to assess the operational efficiency of logistics firms in Türkiye by considering firm attributes. When literature is surveyed in this context, it is found that the existing research addresses the topic in terms of financial performance. Within this approach, many studies in the literature examine the financial performance of logistics firms using multi-criteria decision-making (MCDM) methods. For instance, Alnıpak & Kale (2021) evaluate the financial performance of ten logistics companies listed on BIST Transportation Index with financial ratio data between 2008-2020 through Operational Competitiveness Rating (OCRA) method, taking the impact of Covid-19 into account. The most important factors of various financial ratio categories are identified, and the severe effects of the pandemic are documented. Besides, the liquidity issues resulting from crisis times are emphasized. By employing the Entropy and OCRA methods, İyigün (2024) investigates the financial efficiency of nine firms on BIST Transportation Index with four inputs and four outputs, where the financial structure has been identified as the most significant factor in determining company performance. Erdoğan & Kırbaç (2021) examine the financial efficiency of seven logistics companies listed in Fortune 500 Türkiye from 2015 to 2019, applying MCDM techniques such as Entropy and Weighted Aggregated Sum Product Assessment (WASPAS) on five financial criteria. Export volume is also involved in the analysis, along with financial indicators such as sales, earnings, assets, and equity. The analysis identifies export volume as the most important criterion for financial performance. In the same line, another study applies other MCDM techniques to the seven logistics firms on the Fortune 500 Türkiye list for 2021 (Yürüyen et al., 2023). The seven financial indicators, along with the number of employees and export volume, are weighted with statistical variance (SV), Criteria Importance Through Intercriteria Correlation (CRITIC), Method based on the Removal Effects of Criteria (MEREC), and Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) methods. Then, the companies are ranked based on the performance scores calculated with Mixed Aggregation by Comprehensive Normalization Technique (MACONT) method. The study suggests that decreasing human capital and adopting digital solutions can lead to performance improvements in inefficient companies. Besides, special attention is recommended for profitability management for those firms. Kahramani Koç & Öztürk (2024) assess the financial performance of seven selected companies in BIST transportation and storage sector from 2013 to 2022, using financial ratios. After determining the importance level of criteria with the Entropy technique, the performance scores are calculated with Multi-Attributive Ideal-Real Comparative Analysis (MAIRCA) and Multi-Attributive Border Approximation Area Comparison (MABAC) methods. The results indicate that the profitability and financial performance of companies are influenced by their balance sheet composition, a phenomenon that applies to both individual companies and the sector as a whole. In recent research, the financial efficiency of six logistics companies

traded on BIST Transportation Index is evaluated using selected financial ratios between 2019 and 2023, through the application of Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) methods, with a specific focus on understanding the impact of the pandemic (Öztanır, 2025). Results emphasize the importance of keeping cash reserves for unpredictable market conditions and decreasing debt.

Despite being limited, the DEA method is also used for analyzing the financial performance of logistics companies, in addition to MCDM techniques. As one of the early investigations within this framework, Min & Joo (2006) calculate efficiency scores for operating incomes of the selected US-based 3PL (3rd Party Logistics) companies, where the DEA application is carried out by using accounting data, with the aim of offering deep insights regarding investment decisions and optimization of financial resources to achieve long-term profitability. Sarkar et al. (2025) conduct a cross-country assessment of the operational efficiency of logistics firms in East Asia from 2014 to 2023, using DEA and Malmquist Productivity Index (MPI) methods. The study highlights the role of regional development and high technology adoption as key drivers of operational efficiency in logistics firms, which are also crucial in addressing disruptive events such as COVID-19 pandemic. With a large dataset of logistics firms in Korea for the period between 2006 and 2019, Shamohammadi et al. (2025) measure the firm efficiency by applying SFA method based on a two-input-single-output Cobb-Douglas function and then analyze the drivers of efficiency through Tobit analysis. The findings indicate that innovation activities and holding a quality certificate have a positive influence on operational efficiency, while being listed on stock markets has no significant impact on it.

For Türkiye, Aksungur & Deran (2021) assess the efficiency of eight companies from BIST transportation and storage sector by using financial performance indicators under the DEA framework for the years 2018 and 2019. The findings of the study suggest improvements in current ratio and financial leverage ratios for the inefficient DMUs. In the same line, Kara & Çetinkaya (2022) utilize DEA method with a set of input and output factors consisting of financial ratios to investigate the financial performance of ten companies listed on BIST transportation and storage sector for the year 2021, which involves the Covid-19 period. The study identifies the financial ratios that need to be addressed to achieve full efficiency, with a particular emphasis on the financial leverage ratio. Ersoy & Tehci (2020) use DEA method to assess the financial performance of nine selected Turkish logistics companies listed on Fortune 500 Türkiye for the years 2016 and 2017. The study considers a single firm-specific attribute, namely the number of employees, in addition to financial parameters. The results suggest that better utilization of human capital and total assets is the key to performance improvements. Moreover, benchmarking in terms of supply chain strategy and operations is recommended for inefficient firms. By combining several MCDM techniques,

Işık (2022) evaluates the performance of six logistics firms listed on Fortune 500 Türkiye in 2018. The assessment considers parameters linked to firm attributes, such as the number of employees and export volume, in addition to financial statement items. The findings reveal that export volume, number of employees, and net sales are the most significant factors that determine the performance of logistics firms.

Diverging from the financial ratio analysis, Özkan Özen (2024) identifies factors that can be employed in sustainability performance assessment for the logistics sector and evaluates 10 firms under BIST Transportation Index with various MCDM methods. The study conducts a benchmarking exercise based on compliance with general principles, social and environmental principles, corporate governance principles, and the presence of sustainability reporting. The findings indicate that sustainability reporting and environmental factors are the primary drivers of sustainability performance. Additionally, the companies performing the best are primarily from the aviation sector.

A summary of relevant papers is presented in Table 1, which includes information on the scope and parameters employed. The current research accumulation on the topic suggests a call for further investigation in several aspects. Firstly, the papers primarily focus on financial performance, framing the analysis mainly around financial ratios, without examining firm characteristics that influence efficiency. To the best of author's knowledge, limited studies (Ersoy & Tehci, 2020; Işık, 2022; Yürüyen et al., 2023; Shamohammadi et al., 2025) consider the number of employees as a single representative of firm characteristics, which is used as an input in measuring the efficiency of logistics firms. Methodologically, the papers predominantly utilize MCDM techniques, while frontier methods are used scarcely, despite the relevance of the technical efficiency concept explained earlier. Therefore, this paper aims to fill these gaps by examining the operational efficiency of logistics companies in Türkiye through a frontier method, specifically DEA, and by analyzing firm characteristics that influence efficiency, such as ownership structure, firm size, and expertise, using Tobit analysis. A two-stage DEA application and subsequent Tobit analysis are carried out in an effort to answer the following research questions:

1. What is the framework to measure operational efficiency with input and output factors that represent the operations of a typical logistics firm?
2. How does the efficiency composition vary among different firms?
3. Which resources are being underutilized in terms of operational performance?
4. What firm characteristics influence efficiency? Do any of these have a greater impact on efficiency?

Table 1: Summary of existing research

Study	Country	Scope	Method	Parameters (MCDM)	Outputs (DEA/SFA)	Inputs (DEA/SFA)
Min & Joo (2006)	US	6 3PL companies	DEA		Operating income	Accounts receivables Salaries and wages Operating expenses Property and equipment
Aksungur & Deran (2021)	Türkiye	8 companies from BIST transportation and storage sector	DEA		Current ratio Financial leverage ratio	Return on equity Return on assets
Alnıpak & Kale (2021)	Türkiye	10 transportation companies	OCRA	Liquidity ratios Activity ratios Profitability ratios Leverage ratios Market value ratios		
Ersoy & Tehci (2020)	Türkiye	9 logistics companies from the Fortune 500 Turkey list	DEA		Current ratio Liquidity ratio Financial leverage ratio	Number of employees Total current assets Total Liabilities Short-term liabilities

Erdoğan & Kırbaç (2021)	Türkiye	8 logistics companies listed on the Fortune Turkey	Entropy WASPAS	Net sales EBIT (Earnings before interest and taxes) Total assets Total equity Export volume		
Kara & Çetinkaya (2022)	Türkiye	10 companies from BIST transportation and storage sector	DEA		Profitability ratios Tobin's Q	Current ratio Leverage ratios
Işık (2022)	Türkiye	6 logistics companies on the Fortune 500 Türkiye list	Grey Entropy and FUCOM (Full consistency method) EDAS-M (Evaluation based on distance from average solution in the Minkowski space)	Number of employees Net sales EBIT Change in EBIT Total assets Equity Export volume		
Yürüyen et al. (2023)	Türkiye	7 logistics companies listed on Fortune 500 Türkiye	SV, MEREC, CRITIC and LOPCOW MACONT	Net sales Change in net sales EBIT Change in EBIT Total assets Equity Number of employees Export volume		

Kahramani Koç & Öztürk (2024)	Türkiye	7 companies from BIST transportation and storage sector	Entropy MAIRCA and MABAC	Profitability accounts Profitability ratios		
İyigün (2024)	Türkiye	9 companies from BIST Transportation Index	Entropy OCRA		Profitability ratios	Accounts receivable days Debt to Equity ratio COGS (Cost of goods sold)/ Net sales Operating expenses/Net sales
Öztanır (2025)	Türkiye	6 logistics companies traded on BIST Transportation Index	TOPSIS MOORA	Acid test ratio Turnover ratios Financial leverage ratio Debt to equity ratio Profitability ratios		
Sarkar et al. (2025)	East Asian countries	57 stock-market listed logistics firms	DEA MPI		Revenue Operating Profits	Total Liability Equity
Shamohammadi et al. (2025)	Korea	845 logistics firms	SFA and Tobit		Sales	Total assets Number of employees

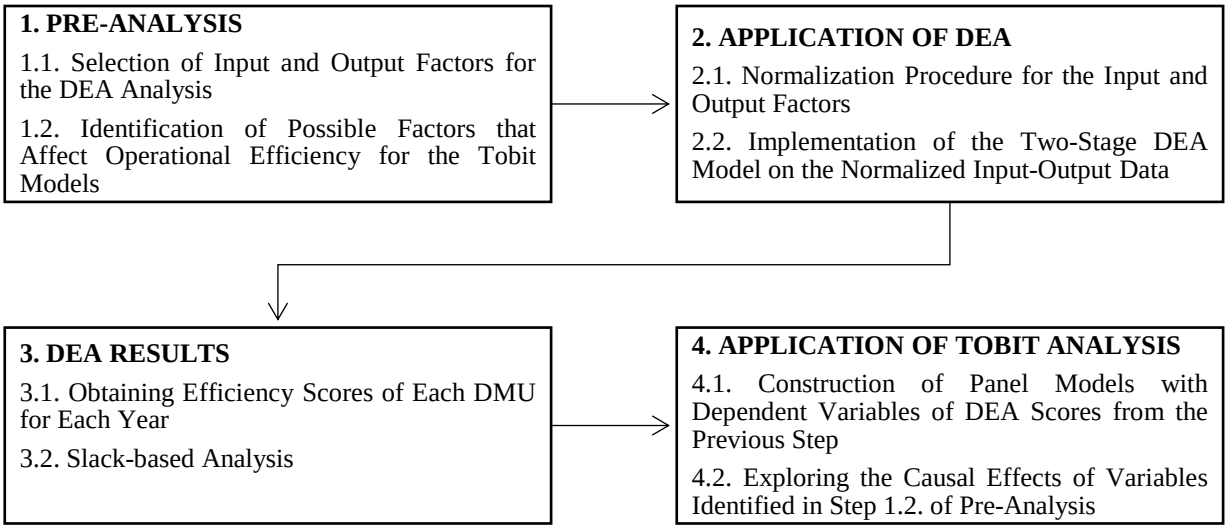
METHODS AND MATERIALS

The research approach of this paper can be summarized in four steps, as shown in Figure 1. This study uses two different but complementary quantitative methods sequentially, specifically DEA and Tobit models. The former method involves calculating efficiency scores to compare the performance of DMUs and evaluate the potential for improvement, while the latter uses regression analysis to understand the causal factors of efficiency. In the initial analysis, a two-stage DEA approach is employed to evaluate the operational performance of logistics firms in Türkiye, utilizing three inputs and one output. By doing so,

the efficiency scores are calculated, and a slack-based analysis is performed to identify areas needing efficiency improvements. In the final step, Tobit analysis is performed to identify which firm characteristics may affect efficiency, using the efficiency scores from the first step as dependent variables.

The methods of DEA and Tobit analysis are often combined in efficiency analysis (Radhi et al., 2025). DEA, as a non-parametric approach, has been a powerful tool for measuring efficiency by utilizing data only, without requiring a presumed functional form (Mergoni et al., 2025). After efficiency scores are obtained with DEA, Tobit analysis is commonly employed to identify the factors influencing efficiency differences among DMUs (Radhi et al., 2025; Ji & Lee, 2010). Tobit regression uses the efficiency scores as dependent variables that are censored at the upper limit (Ji & Lee, 2010). Since the efficiency scores are censored at 1 in this paper, Tobit analysis is suitable for assessing factors that influence operational efficiency in logistics companies.

Figure 1: Research steps of the study



Before applying these two methods, a pre-analysis procedure is conducted in this section of the study, prior to the application of the two-phased research approach, as shown in Figure 1. In this step, the DMUs, along with input and output factors, are selected for the application of the DEA method, following the relevant literature. Similarly, potential causal factors of operational efficiency are identified from the literature to be used in the final step, which is the Tobit analysis.

Performance Measurement

Within the DEA framework, efficiency is represented as a weighted sum of outputs to weighted sum of inputs. By doing so, a diverse set of inputs and outputs is calibrated into a unique efficiency score for

each DMU, based on comparison with the best-performing DMU, as defined by the term relative efficiency (Boles et al., 1995). DEA methodology can be applied using two different approaches: input-oriented and output-oriented models (Ozbugday et al., 2020). The objective of input-oriented models is minimization of inputs while achieving a given level of output, whereas output-oriented models focus on maximizing outputs by using the same quantity of inputs. This paper employs a two-stage output-oriented Data Envelopment Analysis (DEA) approach to obtain efficiency scores for the firms with selected inputs possibly representing operational parameters.

Data envelopment analysis

Data Envelopment Analysis (DEA) is a non-parametric benchmarking technique coined by Charnes et al. (1978), where efficiency is defined as the ratio of weighted output to weighted input, with constant returns to scale (CCR). Later, a DEA model allowing for variable returns to scale (VRS) is developed by Banker et al. (1984), referred to as DEA BCC, to assess entities on the efficient frontier. These two conventional models (CCR and BCC models of DEA) have served as profound tools for efficiency research in both academic and practical fields. However, these models are based on a single production process where inputs generate outputs directly, an assumption which is not consistent with the theory of the firm. To tackle this problem, a novel approach called two-stage DEA model is proposed (see Kao & Hwang, 2008; Chen et al.,2009), where overall efficiency is obtained using a multiplicative approach of first and second stage efficiency. The two-stage DEA has become a more reliable and realistic approach by implementing multiple production processes and linking the two stages (Liu et al., 2020).

For a set of n DMUs D= $\{DMU_1, \dots\dots, DMU_n\}$ which constitute the analysis units, variables x_{ik} represent input and z_{dk} stand for output values respectively for DMU_k in the first stage. The output values z_{dk} are used as input values in the second stage, known as intermediaries. The outputs from the second stage are represented as y_{qk}. Then, as stated in Kao & Hwang (2008), the efficiency of each DMU can be obtained by the multiplication of two individual efficiency procedures, i.e., E_k=$E_k^1 \times E_k^2$. Assuming the output weight in the first stage is the same as the input weight used in the second stage, the overall efficiency of DMU_k can be expressed with the following equation (Liu et al., 2020):

$$E_k = max \sum_{q=1}^{p} u_{qk} y_{qk} \qquad (1)$$

s.t.

$$\sum_{i=1}^{m} w_{ik} x_{ik} = 1,$$

$$\sum_{d=1}^{r} \delta_{dk} z_{dj} - \sum_{i=1}^{m} w_{ik} x_{ij} \leq 0 \qquad j = 1, \dots, n,$$

$$\sum_{q=1}^{p} u_{qk} y_{rj} - \sum_{d=1}^{r} \delta_{dk} z_{dj} \leq 0 \qquad j = 1, \dots, n,$$

$$u_{qk}, \delta_{dk}, w_{ik} > 0 \qquad q = 1, \dots, p, \quad d = 1, \dots, r, \quad i = 1, \dots, m.$$

After decomposition, the following linear programming model can be solved to calculate first stage efficiency values of E_k^1

$$E_k^1 = max \sum_{d=1}^{L} \delta_{dk} z_{dk} \qquad (2)$$

s.t.

$$\sum_{i=1}^{m} w_{ik} x_{ik} = 1,$$

$$\sum_{q=1}^{p} u_{qk} y_{qk} - E_k \times \sum_{i=1}^{m} w_{ik} x_{ik} = 0$$

$$\sum_{d=1}^{r} \delta_{dk} z_{dj} - \sum_{i=1}^{m} w_{ik} x_{ij} \leq 0 \qquad j = 1, \dots, n,$$

$$\sum_{q=1}^{p} u_{qk} y_{rj} - \sum_{d=1}^{r} \delta_{dk} z_{dj} \leq 0 \qquad j = 1, \dots, n,$$

$$u_{qk}, \delta_{dk}, w_{ik} > 0 \qquad q = 1, \dots, p, \quad d = 1, \dots, r, \quad i = 1, \dots, m.$$

Hence, the second stage efficiency can be defined as $E_k^2 = E_k \,/\, E_k^1$.

The examination in this study focuses on calculating output-oriented efficiency scores, with the objective of maximizing attainable output. A DMU is deemed efficient if its efficiency score equals 1 (or

100%), which indicates its position on the efficient frontier. The degree of inefficiency of a DMU increases as its score diverges from 1. Therefore, the extent of inefficiency is determined by the gap between the DMU's score and the efficient frontier, which serves as the benchmark for comparison.

This paper specifically concentrates on measuring technical efficiency, which refers to a DMU's ability to achieve a specific level of output using fewer inputs or to produce a greater output with the same amount of inputs.

Selection of DMUs, inputs and outputs

The analysis unit comprises the firms included in BIST Transportation Index, which consists of twelve companies listed on the Public Disclosure Platform (KAP, 2025). In this study, DEA is applied to evaluate the operational efficiency of six logistics companies selected based on data availability for the case of Türkiye. Firms that lack any data are eliminated from the DMUs dataset to address the issue of missing data, as a typical remedy suggested for such cases (see Sarkis, 2007).

Table 2: Input and output variables

Inputs	Output
Cost of Sales	Revenue
Operating Expenses	
Inventories	

Table 2 presents the input and output variables. The input variables include cost of sales (COS), operating expenses (OE), and inventories (INVEN). In a survey exploring the performance of automotive manufacturers and their suppliers, Brandenburg & Hahn (2021) consider cost of goods sold and operating capital, which includes inventories, as input variables. Based on this rationale, cost of sales and inventories are regarded as resources that generate revenue for the service business of logistics. Additionally, operating expenses are considered as another input factor, following Min and Joo (2006), İyigün (2024), and Darji and Dahiya (2023). This factor is calculated by adding marketing and selling expenses to general operating expenses. Considering business operations as the primary indicator of firm performance, this study uses Revenue (REV) as the output factor, in line with Darji & Dahiya (2023) and Min & Joo (2006). All variables are downloaded from the Fintables database (Fintables, 2025).

In DEA methodology, the number of DMUs is important for discrimination power, and one of the rules suggested for the minimum number of DMUs is the product of the number of input and output factors

(Sarkis, 2007). In this study, the number of DMUs, which is six, exceeds the minimum required by this rule, which is three. The analysis period spans from 2019 to 2024. The application is carried out using Stata 14 program.

Tobit Analysis

Tobit regression analysis is the most widely used technique in the literature for identifying factors that influence efficiency differences among DMUs (Ji & Lee, 2010). This model allows right- or left-censoring in the evaluation of potential interactions between the dependent and independent variables. More specifically, the values are censored above or below a predefined threshold where dependent variable ranges within a given interval. Therefore, this approach is suitable for the second-phase analysis of this paper, as it involves evaluating the causal factors of efficiency using efficiency scores as dependent variables, which range from 0 to 1.

Tobit model estimates a latent variable ϑ_{it}^{*} with the following general representation:

$$\vartheta_{it}^{*} = X_{it}'\beta + \varphi_{it} + \varepsilon_{it}\ ,\ \varphi_{it} \approx N(0,\sigma_{\varphi}^{2}) \text{ and } \varepsilon_{it} \approx N(0,\sigma_{\varepsilon}^{2}) \qquad (3)$$

where i denotes the cross-sectional units $(1, \ldots . n)$, t represents time $(t = 1, \ldots . T)$, where X_{it} is a vector of explanatory variables, and β is a vector of coefficients. φ_{it} stands for random effects and ε_{it} is the error term. The observed efficiency scores, ϑ_{it}, represent potential censoring in the latent variable ϑ_{it}^{*} with the following equation (McDonald, 2009):

$$\vartheta_{it} = \begin{cases} \vartheta_{it}^{*}, & 0 < \vartheta_{it}^{*} < 1 \\ 0, & \vartheta_{it}^{*} \leq 0 \\ 1, & \vartheta_{it}^{*} \geq 1 \end{cases} \qquad (4)$$

In the last phase of analysis, this study conducts a Tobit regression analysis, which offers a censored structure (Tobin, 1958). In this analysis, multiple random effects models are estimated, including factors that reflect firm characteristics. These factors are selected based on the literature. As one of the potential variables, firm size can be a significant factor in operational performance, given the success of multinationals worldwide (Kim et al., 2021; Jeong et al., 2025). Hence, the value of total assets is also involved in the analysis, following the common practice in the literature (e.g., Handoyo et al., 2023; Jeong et al., 2025; Ersoy & Tehci, 2024). To answer the research questions of this study, equity and total fixed assets are taken as alternative measures for firm size. The data for these three firm size variables is obtained from the Fintables database (Fintables, 2025), where the data is denominated in Turkish Lira. As another potential influencer, the ownership structure is also considered, following Çelen (2013), with a dummy

variable taking the value of 1 for foreign ownership and 0 otherwise. In addition, firm age is also taken into account as an indicator of firm expertise, based on previous research including Handoyo et al. (2023) and Jeong et al. (2025). Moreover, the factor of employee number is reported to be instrumental in the operational efficiency of healthcare business (Habib & Shahwan, 2020) and construction sector (Ersoy & Tehci, 2024). Therefore, in line with the scope of this paper, the number of employees is also taken as another factor that might affect the operational efficiency of companies in the service business of logistics. The data for ownership structure, firm age and number of employees are compiled from the financial and annual reports on the websites of the selected companies, the former variable being a binary variable (0 or 1) and the latter two being denoted in numbers. Stata 14 program is employed in the Tobit analysis.

APPLICATION AND FINDINGS

This study primarily uses two methods, with Tobit analysis performed after DEA application. It firstly assesses the efficiency of six logistics firms selected from BIST Transportation Index for the period between 2019 and 2024 and then attempts to unveil the factors that affect these efficiency scores. To do that, a normalization procedure is applied before the application of DEA. Then, two-stage DEA is used for efficiency and slack-based analysis. In the final phase of analysis, the paper examines the determinants of operational efficiency in logistics firms using Tobit analysis.

Different factors are considered in DEA and Tobit analysis for several reasons. First, including all variables as input factors in DEA would decrease the discriminatory power, as the number of DMUs considered in this study would fall short of the required number (see Sarkis, 2007). Secondly, analyzing how the input factors from the earlier phase influence efficiency scores would violate the main assumptions of regression analysis because they are already used in measuring efficiency.

Normalization Procedure

Table 3 presents the descriptive statistics of raw data for input and output variables, which are in large magnitudes. Besides, there are large imbalances across values, as observed from the ranges and standard deviations in Table 3.

Table 3. Descriptive statistics of the input and output factors

	Obs	Mean	Std. Dev.	Min	Max
REV	36	59,100,000,000	153,000,000,000	41,300,000	745,000,000,000
COS	36	46,600,000,000	121,000,000,000	30,100,000	603,000,000,000
OE	36	5,610,000,000	16,000,000,000	1,206,886	79,000,000,000
INVEN	36	1,580,000,000	4,430,000,000	345,351	23,700,000,000

Source: Fintables (2025)

The data characteristics require a standardization procedure for the variables. Since there are significant variances across DMUs, a normalization procedure is applied to the data to correct large imbalances. Following Aparicio & Santín (2025) and Sarkis (2007), the dataset is mean-normalized to obtain a balanced magnitude. In this process, values are scaled to the mean of each input and output factor, thereby transforming the dataset's range to the interval between 0 and 1. The descriptive statistics are provided in Table 4 for the normalized data. Here, it can be seen that the means are standardized to 1 for all variables, and the standard deviations show a more balanced distribution.

Table 4. Descriptive statistics of the normalized input and output factors

Variable	Obs	Mean	Std. Dev.	Min	Max
REV	36	1	2.59023	0.00070	12.61923
COS	36	1	2.59562	0.00065	12.92562
OE	36	1	2.84533	0.00022	14.07834
INVEN	36	1	2.80358	0.00022	14.97119

Source: Author's work on the data obtained from Fintables (2025)

Table 5. Pairwise correlation

	REV	COS	OE	INVEN
REV	1			
COS	0.9994*	1		
OE	0.9952*	0.9960*	1	
INVEN	0.9822*	0.9872*	0.9886*	1

Note: * indicates significance at 5%.

Source: Author's work on the data obtained from Fintables (2025)

Table 5 shows the pairwise correlation among input and output factors. All factors are positively and strongly correlated, as indicated by the coefficients in Table 5.

DEA Application

This study uses an output-oriented DEA model with three inputs and a single output, assuming constant returns to scale (CRS) due to data normalization. The efficiency scores calculated are presented both annually and as an average over the six-year period in Table 6. The firms in the sample are coded for data privacy.

Table 6. Efficiency scores

	2019	2020	2021	2022	2023	2024	Average (2019-2024)
DMU 1	0.7992	1	1	1	1	1	0.9665
DMU 2	0.7050	0.5610	0.5334	0.7377	0.8710	0.9795	0.7313
DMU 3	0.5846	0.4141	1	1	0.6858	1	0.7807
DMU 4	0.8397	0.3321	0.6159	0.6988	0.7577	0.9196	0.6940
DMU 5	0.6067	0.4448	0.4661	0.5163	0.7561	0.8038	0.5989
DMU 6	1	1	1	1	1	1	1
Average	**0.7559**	**0.6253**	**0.7692**	**0.8255**	**0.8451**	**0.9505**	**0.7952**

Based on the results in Table 6, DMU 6 operates at full efficiency throughout the entire analysis period, ranking as the top-performing logistics company. This firm is capable of achieving the highest gains from operational inputs consumed in the production of services that the company offers. Following that, DMU 1 operates at full efficiency during the analysis period, except in 2019. DMU 3 ranks in third place with an average score of 0.7807 between 2019 and 2024. DMU 2, DMU 4 and DMU 5 are the bottom performers in terms of operational efficiency. Looking at the average efficiencies across years, the lowest average efficiency is observed for the year 2020. This decline is possibly related to the Covid-19 era, which is marked by significant disruptions in public investments, as well as volatility and structural changes in trade (Hayakawa & Mukunoki, 2021; OECD, 2022). The effects of the pandemic have hit trade more severely, especially in the first quarter of 2020, causing critical challenges for the logistics companies (Senir & Büyükkeklik, 2020). The detrimental impact of the pandemic includes, but is not limited to, the bullwhip effect, capacity constraints, and rising logistics costs (Ozkanlisoy, 2021). Hence, efficiency scores are at their lowest in the breakdown year of the pandemic, 2020. Despite the damaging consequences of Covid-19, two firms managed to be on the efficient frontier. This can be explained mainly by the competency of these firms in two areas. The first area is the efficient utilization of tax incentives, credit supports, and labor incentives offered under the 'Economic Stability Shield Program,' announced in 2020 to combat the negative effects of the pandemic on the private sector (Presidency of the Republic of Türkiye, 2020). The

second area covers a more strategic and managerial perspective, which involves a managerial vision that enables adaptability to changing market conditions.

Table 7. Slack-based improvements analysis

					Input Slacks		
		Rank	**Efficiency Score**	**Benchmark**	**COS**	**OE**	**INVEN**
2019	DMU 1	3	0.7992	DMU 6	0.0043	-	0.0022
	DMU 2	4	0.7050	DMU 6	-	0.0221	0.0005
	DMU 3	6	0.5846	DMU 6	-	0.0004	0.0001
	DMU 4	2	0.8397	DMU 6	0.0315	0.0525	-
	DMU 5	5	0.6067	DMU 6	-	0.7814	0.3883
	DMU 6	1	1	-	-	-	-
2020	DMU 1	2	1	DMU 6	0.0183	-	0.1034
	DMU 2	3	0.5610	DMU 6	-	0.0155	0.0019
	DMU 3	5	0.4141	DMU 6	-	0.0003	-
	DMU 4	6	0.3321	DMU 6	-	0.0112	0.0035
	DMU 5	4	0.4448	DMU 6	-	0.3346	0.4772
	DMU 6	1	1	-	-	-	-
2021	DMU 1	3	1	DMU 3	0.0189	-	0.1008
	DMU 2	5	0.5334	DMU 3	-	0.0112	0.0006
	DMU 3	1	1	-	-	-	-
	DMU 4	4	0.6159	DMU 3	0.0570	0.0094	-
	DMU 5	6	0.4661	DMU 3	-	0.2269	0.5236
	DMU 6	2	1	DMU 3	0.0002	-	0.0001
2022	DMU 1	3	1	DMU 6	0.1010	-	0.7562
	DMU 2	4	0.7377	DMU 3	0.0109	0.0355	-
	DMU 3	1	1	-	-	-	-
	DMU 4	5	0.6988	DMU 3, DMU 6	0.0838	-	-
	DMU 5	6	0.5163	DMU 3, DMU 6	-	0.4088	0.4772
	DMU 6	1	1	-	-	-	-

2023	DMU 1	2	1	DMU 6	0.1419	-	0.6273
	DMU 2	3	0.8710	DMU 6	-	0.1168	0.0330
	DMU 3	6	0.6858	DMU 6	-	0.0051	0.0013
	DMU 4	4	0.7577	DMU 6	-	0.1399	0.2419
	DMU 5	5	0.7561	DMU 6	-	5.1870	3.9324
	DMU 6	1	1	-	-	-	-
2024	DMU 1	3	1	DMU 6	0.0884	-	0.3764
	DMU 2	4	0.9795	DMU 6	-	0.2100	0.0377
	DMU 3	2	1	DMU 6	-	0.0074	0.0018
	DMU 4	5	0.9196	DMU 6	-	0.4073	0.5503
	DMU 5	6	0.8038	DMU 6	-	8.0384	9.7847
	DMU 6	1	1	-	-	-	-
Average					**0.0505**	**0.7629**	**0.7676**

Note: Small numbers that are equal to or lower than 10^{-6} are not reported.

Table 7 presents a slack-based analysis for each firm, highlighting potential improvements in input factors from 2019 to 2024. With the exception of year 2021, DMU 6 shows optimal utilization of its resources, leaving no room for improvement. Table 7 also shows the references for inefficient DMUs, with DMU 3 and DMU 6 identified as benchmarks. In the context of benchmarking, for instance, the two-stage DEA model designates DMU 6 as the benchmark for DMU 1 in 2019. To illustrate the interpretation of efficiency scores based on the same DMU in the same year, the efficiency score of 79.92% suggests that resources allocated for COS, OE, and INVEN could be reduced by 20.08%. Additionally, DMU 1 has slack for certain inputs, indicating that performance can still be improved with additional input reductions based on the slack values, even after cutting all inputs by 20.08%. Overall, the lowest slack values are observed in COS, which might be associated with the relative ability of the firms to offer their services at an acceptable cost. The highest average slack for INVEN should be taken as a sign of stock mismanagement. This implies that firms keep an excess supply of materials beyond what is necessary, whether the inventory consists of office supplies or goods to be sold. Additionally, the average slack for OE is also high, which might indicate that marketing, distribution, and administrative tasks are performed below optimal levels.

Unveiling the Causal Factors of Operational Efficiency

In the second phase, this paper seeks to identify the factors that affect the operational efficiency of logistics firms. To do that, Tobit regressions are performed using independent variables selected based on

previous literature. The dependent variables consist of the scores obtained by the DEA method. The results of the Tobit models are presented in Table 8.

Table 8. Results of the Tobit models

	Model 1	Model 2	Model 3	Model 4
Ln (Total Assets)	0.1832*			
	[0.00]			
Ln (Fixed Assets)				-0.0375***
				[0.10]
Ln (Equity)		-0.0821*	-0.0776*	
		[0.00]	[0.00]	
Ownership Structure	0.4152***	-0.0727		0.3542
	[0.10]	[0.80]		[0.29]
Firm Age	-0.0314*	-0.0077	-0.0091*	-0.0174***
	[0.00]	[0.31]	[0.00]	[0.06]
Number of Employees	0.0000	0.0000**	0.0000***	0.0000**
	[0.30]	[0.02]	[0.06]	[0.04]
Constant	-2.0081*	2.9293*	2.8769*	2.2592*
	[0.01]	[0.00]	[0.00]	[0.00]
Wald $\chi 2$ Test	Wald $\chi 2(4)$ 30.04*	Wald $\chi 2(4)$ 32.25*	Wald $\chi 2(3)$ 26.54*	Wald $\chi 2(4)$ 17.02*
	[0.00]	[0.00]	[0.00]	[0.00]
Log Likelihood	-4.2446	2.3555	-3.4019	-8.2768

Note: *, **, *** represent significance at 1%, 5% and 10% respectively.

Four different models are run to identify the causal factors of operational efficiency, where large magnitude variables (Total Assets, Fixed Assets, and Equity) are involved in natural logarithmic form. In Model 1, the positive coefficient of Total Assets is significant at 1%, suggesting that financial resources of companies are important factors that enhance operational efficiency. This might be explained as follows: a firm with greater economic capacity can invest more in digitalization, staff training, and new business models, which ultimately increases process efficiency throughout the company. In Models 2-3, the coefficients of Equity are statistically significant but with negative values. Regarding Equity, tied-up capital in the form of financial instruments may fuel the company's growth, but this can also worsen operational efficiency when the business operates as usual. In Model 4, the negative coefficient for Fixed Assets

indicates an inverse relationship between Fixed Assets and operational performance. As a possible explanation for this negative effect, significant funds may be allocated to fixed assets, such as property and equipment; however, the gains from such initiatives may fall short of the dedicated resources.

As another noteworthy finding, Firm Age is statistically significant in all models except Model 2, with negative coefficients. This inverse linkage means that sales generation declines as a firm operates in the logistics sector for a longer period. The possible cause for this impact can be adapting an excessive growth strategy over years, inharmonious with the management skills of the firm, coupled with increasing integration of bureaucratic work in operations. The Number of Employees is another significant factor, except in Model 1, which has an incremental positive influence on performance relative to other variables. Ownership Structure is found to be significant in only Model 1 at 10% significance when the factor of Total Assets is included. So, whether a firm has foreign owners or not becomes an influential factor in operational efficiency when considered together with the value of assets a company owns. Regarding model diagnostics, Wald test results indicate overall model significance at the 1% level for all models.

CONCLUSION AND DISCUSSION

An important aspect of performance measurement is the examination of operational efficiency resulting from overall business processes, in addition to financial performance. In this context, the aim of this paper is to analyze the operational efficiency of logistics firms and to identify the firm characteristics that impact efficiency, using a two-phase approach that incorporates DEA and Tobit analysis techniques. This focus seeks to contribute to the literature in three aspects. Firstly, it investigates the performance with operational parameters, with the goal of establishing a supply chain orientation in the analysis, complementing the financial performance evaluation commonly found in the literature. Secondly, it attempts to identify the causes of performance in logistics firms, particularly those associated with firm characteristics. Lastly, a two-phase approach is employed in the analysis, where DEA is used as a frontier model, and Tobit analysis is conducted in the subsequent phase as a censored regression model.

This study examines the operational efficiency of six logistics firms selected from BIST Transportation Index for the period from 2019 to 2024. To do that, an output-oriented two-stage DEA method is applied after the normalization of the input-output data. The selected input variables are cost of sales, operating expenses and inventories, while the output variable is sales revenue. In the second stage, this paper seeks to pinpoint the causes of efficiency scores through Tobit analysis.

The efficiency analysis yields an average score of 0.7952 during the analysis period. This is, on average, equivalent to 79.52% efficiency, which means that all input factors can be reduced by 20.48% without lowering any additional input or output. Regarding the performances, firms exhibit different efficiency levels, in line with the efficiency compositions obtained in the previous papers, such as Kara & Çetinkaya (2022), Ersoy et al. (2020), and Aksungur & Deran (2021). As the top performer, DMU 6 operates at full efficiency throughout the period under investigation. The performance evaluation also points to DMU 3 and DMU 6 as referents for the inefficient firms. The slack-based improvements particularly highlight the need for better management of operations and inventory. Tobit analysis reveals some potential factors that affect operational efficiency. The positive influence of total assets and number of employees contradicts the negative associations found in Ersoy & Tehci (2024). Çelen (2013) has found a significant positive relationship between ownership structure and efficiency scores of electricity distribution companies. Regarding the findings of this paper, the analysis supports this positive association for logistics firms only in a single model, where no significant link is found in the other two models. Another notable finding is that the negative impact of firm age on operational efficiency aligns with the results of Jeong et al. (2025).

The results reveal important managerial and practical implications. To begin with, there is heterogeneity in the performance of logistics firms, as observed with significant efficiency gaps among the companies under investigation. This reveals that individual companies require tailored strategies for success, as their characteristics vary significantly from one another. Hence, strategy development should prioritize alignment with the company's competence and capacity, as well as its long-term goals. Moreover, integrating the principles of continuous improvement, i.e., kaizen, into activities at every stage of the company is essential to enhance performance (Siew Mui et al., 2022). In line with kaizen principles, benchmarking exercises can help identify efficiency gaps of a firm, compared to the best practices in the logistics sector (Gonzalez et al., 2025). Integrating kaizen philosophy and benchmarking into company strategy can provide a long-term commitment to continuous development, agility, and alignment (Sarkis, 2001). Such strategic endeavors can benefit small-scale and family-owned businesses even more by implementing a holistic supply chain orientation from top to bottom. In terms of efficiency improvements, inventory management has been identified as the most important area, as this function plays a crucial role in ensuring seamless operations, cost reduction, and effective resource utilization. To improve inventory management performance, logistics companies can adopt advanced ERP (Enterprise Resource Planning) systems to enhance inter-functional coordination and enable supplier relationship management (Fang & Chen, 2022). Additionally, more traditional solutions include regular audits and the use of stock control tools like ABC analysis and stock alerts for effective inventory management. In addition, operations management can be considered as another area that needs attention for efficiency improvements. Since it is

directly related to core business activities, its improvement requires reconfiguring business processes in logistics firms. To achieve this, firms should conduct business process analysis using well-established techniques, including value analysis, gap analysis, impact analysis, and predictive analysis. Based on the evaluations, business processes can be refined by considering various alternatives such as automation of manual processes, eliminating waste, outsourcing, leveraging technology etc., to achieve performance improvement.

Several implications can also be drawn from the evaluations on the driving factors of operational efficiency for logistics companies. To begin with, investing in assets or equity can increase the value of a share on stock exchange, boosting capitalization. However, the impact mechanism is different in terms of operational performance. Logistics companies should invest in cash equivalents, which are essential for running daily logistics operations smoothly. Long-term assets negatively affect operational performance due to the long-term debts incurred for these assets. Additionally, shareholders' equity is expected to have an inverse relationship with operational efficiency, underscoring the importance of working capital for logistics firms. The negative impact of firm age might suggest that logistics companies should maintain flexibility and responsiveness strategies at the start, to avoid organizational rigidity that could impair operational performance as they mature (see Loderer & Waelchli, 2010). Regarding the positive effect of employee number, since logistics business might continue to be labor-intensive for a considerable period, companies should focus on retaining and upskilling their employees.

This paper has several limitations. Firstly, it analyzes the operational performance of six logistics companies listed on BIST Transportation Index in Türkiye. Secondly, the time span under examination involves a narrow range of six years. Thirdly, the input-output factors in DEA method and the independent variables in Tobit models might be relatively small. Finally, the paper relies solely on secondary data, and some variables are collected from the reports on the websites of selected firms. Future research can conduct a cross-country analysis on the performance of logistics firms in the context of emerging markets, including Türkiye. Moreover, the period of analysis can be extended. In that way, a broader set of input-output factors can be included in the DEA method, and more factors representing firm attributes can also be evaluated. Future research can also focus on the efficiency comparison of different fields of the logistics sector, upon accessibility of large databases offered by various organizations. Additionally, prospective studies can examine the gaps in operational efficiency across various BIST sectors. As a last recommendation, the analytical framework can be enriched by including expert opinions from practitioners in the logistics business in prospective studies.

AUTHOR STATEMENT

The author declares that all contributions to this manuscript were made solely by the author. The author also declares that there are no conflicts of interest.

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