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Financial Performance Analysis of Borsa Istanbul-Listed Automotive Firms: A DEA and Benchmarking Approach

Hatice CENGER[1]

Abstract

This study aims to comparatively analyze the financial performances of firms in the automotive sector using Data Envelopment Analysis (DEA), distinguishing between firms with effective debt management and those without. It seeks to propose recommendations for less efficient firms to improve their efficiency by benchmarking them with more efficient counterparts. In this context, the relative financial performance of automotive sector companies traded in Borsa Istanbul (BIST)i n 2022 was measured with a mathematical programming-based Data Envelopment Analysis (DEA). As a result of the study, companies that achieved relative efficiency; While TAOSA, FROTO, TTRAK and DOAS, relatively inefficient companies were OTKAR, KARSN, ASUZU and TMSN. According to the analysis results, inefficient companies were benchmarked by efficient enterprises. In this benchmarking application, any changes to be made to input variables (Total Debt/Total Assets, Net Debt/EBITDA) and output variables (Net Profit/Sales, Net Profit/Total Assets, Net Profit/Equity) were calculated in MS Excel using financial statements obtained from the Public Disclosure Platform (PDP).

Anahtar Kelimeler: Automotive Industry, Data Envelopment Analysis, Benchmarking, Efficiency

Borsa İstanbul'da İşlem Gören Otomotiv Firmalarının Finansal Performansının VZA ve Benchmarking ile Değerlendirilmesi

Öz

Bu çalışma, otomotive sektöründe yer alan firmaların Veri Zarflama Analizi (VZA) yoluyla, etkili borç yönetimine sahip firmalar ile bu özelliğe sahip olmayan firmaların finansal performanslarını karşılaştırmalı olarak analiz etmek, birbiri ile benchmarking, bu konuda verimli olmayan firmaların daha verimli olması için önerilerde bulunmaktır. Bu bağlamda çalışmada; Borsa İstanbul'da (BIST) işlem gören otomotive sektörüne ait firmaların 2022 yılına ait görece mali performansları matematiksel programlama tabanlı Veri Zarflama Analizi yöntemiyle ölçülmüştür. Çalışma sonucunda görece etkinliğe ulaşan firmalar; TAOSA, FROTO, TTRAK ve DOAS olurken görece verimsiz firmalar OTKAR, KARSN, ASUZU ve TMSN olmuştur. Analiz sonuçlarına göre verimli olmayan firmalar verimli firmalar ile benchmarking yapılmıştır. Girdi-çıktı bileşenlerinde yapılması gereken değişiklikler oransal olarak belirtilmiştir. uygulamada Girdi (Toplam Borç/Toplam Aktif, Net Borç /FAVÖK) ve çıktı (Net kar/Satışlar, Net kar/Toplam Aktif, Net kar/Özsermaye) değişkenleri kamu aydınlatma platformundan (KAP) elde edilen mali tablolar yardımı ile MS EXCEL'de hesaplanmıştır.

Keywords: Otomotive Sektörü, Veri Zarflama Analizi, Kıyaslama, Etkinlik

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[1] Öğr.Gör.Dr., Muğla Sıtkı Koçman University, Fethiye Faculty of Business Administration, cenger@mu.edu.tr,
ORCID: 0000-0002-5703-2201

Introduction

Organizations typically set strategic goals and objectives to improve their performance over a defined period. As part of monitoring and control processes, auditors and managers assess progress toward these objectives. A critical challenge is determining how to achieve optimal performance, both organizationally and financially, amidst competitive pressures and internal constraints

Periodic updates of performance measurement and evaluation, presenting them in a clear, accurate, and concise manner, is essential for attracting new investors and enhancing the company's reputation. Recently, the use of performance indicators as an assessment of the organization's goals has been increasing. Despite the undeniable importance of non-financial factors in the analysis and evaluation of organizational performance, it is clear that financial analysis remains the main focus of many studies. According to Omaki (2005), despite the limitations, numerous studies have shown that accounting-financial performance measures are valid as reasonable predictors of corporate performance.

Performance measurement aims to continuously monitor the efficiency and economy of company operations and provide information for corporate decision-making. Benchmarking is a way of comparing corporate performance with that of competitors. Nowadays, financial indicators are commonly used tools for corporate performance analysis. Adequate performance evaluation and comparability require a method that allows the use of both quantitative and qualitative characteristics, which can measure corporate performance in a complex way. Data Envelopment Analysis (DEA) is such a method. DEA is a method that allows for measuring, ranking, and comparing the performance of companies (Fenyves et al., 2015). Using DEA for benchmarking provides a feasible assessment in terms of goals that represent best practices.

DEA is particularly valuable for benchmarking because it identifies the most efficient decision-making units (DMUs) as benchmarks for others, offering practical improvement targets rather than just abstract scores. By constructing an efficient frontier based on observed data, DEA not only highlights the relative standing of each firm but also provides a roadmap for underperforming units to achieve best practices (Cook and Zhu, 2005). Unlike traditional parametric methods that impose specific functional forms, DEA's non-parametric nature enables it to flexibly adapt to the complexities of real-world corporate operations, making it a preferred tool for comparative performance evaluation across various industries.

This study primarily focuses on the financial performance of automotive companies listed on the ISE. Performance is examined globally in terms of efficiency and profitability. However, in the empirical section, more emphasis is placed on efficiency. In this context, a two-stage model has been selected to investigate the companies' performance: In the first stage, DEA efficiency indices are calculated based on the input-oriented BCC model to perform super-efficiency analysis to assess the performance level of the target. In the second stage, based on the analysis results, relatively inefficient companies are compared with relatively efficient ones. Changes to be made in the input/output combinations are expressed proportionally in this application.

The purpose of this study is to identify gaps, differences, strengths, and weaknesses among comparison partners in the sector using the findings from the comparative analysis and the information from industry leaders to improve the financial performance of companies and enhance their efficiency in managing financial resources. Our focus is particularly on financial sustainability, which relates to a company's long-term financial health, ability to meet financial obligations, maintain profitability, and support operations and growth in the long run.

When reviewing the literature, it has been observed that most studies on the automotive sector listed on Borsa Istanbul have utilized the DEA method; however, sufficient emphasis has not been placed on comparisons. Our study addresses this gap by highlighting the benchmarking feature of the DEA method, which identifies the successful firms in the sector. It explains why low-efficiency firms are inefficient compared to efficient ones and how they can improve their efficiency through proportional changes in input-output variables.

The reason for focusing on the automotive sector in this study is that automotive companies hold a high level of fixed assets, indicating that the automotive industry is highly competitive, has high leverage ratios, and is capital-intensive. This increases the use of external financing. Due to high fixed and operating costs, automotive sector companies need to maintain a consistent level of financial performance to sustain their position in the industry.

The study consists of two parts: theoretical and practical. In the first section, after explaining the theoretical basis of DEA and benchmarking, the financial data of automotive companies listed on the ISE are used to perform a data envelopment analysis, identifying inefficient units and making comparisons. Proportional changes required in inefficient units are indicated, and information is provided regarding the extent to which these changes will be implemented.

Empirical Literature

Most studies related to the automotive sector listed on the Istanbul Stock Exchange use the DEA method, and these studies have only identified the efficient and less efficient DMUs without considering the changes needed in input and output variables for inefficient firms to become relatively efficient. These studies include: Yıldız (2006); Özdemir and Düzgün (2009); Yaylalı and Çalmaşur (2014); Nurcan and Kaya (2016); Tatlı and Bayrak (2016); Gedik, Koçarslan et al. (2017); Şahin and Akkoyuncu (2019); Bardi (2023); Cenger and Sarıyer (2022).

Data Envelopment Analysis (DEA) has been widely used not only as an efficiency measurement tool but also as a robust benchmarking methodology across various industries. The literature supports DEA's role in identifying best-performing decision-making units (DMUs) and in providing performance targets through frontier analysis. Cook and Seiford (2009) explicitly refer to "DEA benchmarking" and describe how DEA enables the identification of high-performing DMUs, thereby offering practical benchmarks for underperforming ones. Similarly, Thanassoulis (2001) devotes an entire section to DEA's benchmarking function, highlighting how inefficient DMUs can be projected onto the efficient frontier, allowing for strategic performance improvement.

Empirical applications of DEA as a benchmarking tool are also well-documented. Collier and Storbeck (1993) applied DEA in the telecommunications industry, while Bell and Morey (1995) used it in corporate travel management. Barr and Seiford (1994) evaluated banking and financial institutions, and Athanassopoulos and Ballantine (1995) used DEA for comparative analysis in the food industry. Morey and Dittman (1995) assessed the operational efficiency of fifty-four hotels, offering improvement pathways for the less efficient ones. Similarly, Sigala (2003) investigated best practices in the online marketing strategies of Greek hotels, providing benchmarking-based suggestions. Further applications can be found in Tepe (2006), Lim et al. (2011), Gülcü and Cenger (2013), Didehkhani et al. (2019), Atalay and Vatansever (2020), and Cenger (2023), all of whom employed DEA as a benchmarking instrument.

These theoretical insights and practical applications confirm the suitability of DEA in studies focusing on relative efficiency and performance benchmarking, particularly within sector-specific analyses such as the automotive industry. While DEA has been frequently employed in various sectors, its limited application as a benchmarking tool in the automotive industry highlights the originality and contribution of this study. By identifying efficient decision-making units, DEA creates benchmarks that serve as performance references, thereby strengthening competitive positioning and supporting continuous improvement. In this context, inefficient units are not only evaluated but also provided with concrete improvement suggestions derived from frontier-performing firms. This benchmarking approach enables underperforming firms to systematically progress toward the efficiency frontier, promoting sectoral learning and strategic alignment.

Data and Methodology

In the study, the DEA benchmarking model, used to measure and improve the relative efficiency of firms, is applied. Due to the nature of the dataset, the "convex, variable returns to scale, input-oriented BCC model, and radial input-oriented super-efficiency model" have been preferred. The input/output variables of DMUs for the year 2022 were calculated in Excel using the balance sheet and income statement obtained from the Public Disclosure Platform (KAP). The data were analyzed using EMS (Efficiency Measurement System) software, developed for academic research. All statistical analyses, including correlation and regression tests, were performed using IBM SPSS Statistics software (version 27).

Benchmarking and DEA Comparison

Benchmarking is traditionally defined as a systematic process of comparing an organization's practices, processes, and performance against industry leaders (Camp, 1989; Eyrich, 1991; Kleinhans et al., 1995). Originating in Japanese manufacturing, it was later adopted globally as a tool for identifying best practices and setting performance targets (Anderson & Peterson, 1993). Unlike conventional benchmarking which emphasizes qualitative insights into how goals are achieved (Moseng, 1995) this study integrates quantitative DEA-based benchmarking to assess financial efficiency.

Benchmarking can be particularly helpful in operational efficiency improvement, as it provides organizations with new strategies and practices to adopt in order to boost their performance. According to Bergeron (2003), it involves studying the best practices in an industry to improve operational performance. In this study, benchmarking is considered within the broader scope of comparing firms' relative performance, particularly focusing on financial efficiency.

In contrast, DEA complements traditional benchmarking by offering a data-driven approach to efficiency measurement. It evaluates how effectively firms convert inputs (e.g., assets, liabilities) into outputs (e.g., revenue, profit) and identifies underperformers relative to an efficiency frontier (Charnes et al., 1994). While traditional benchmarking focuses on strategic emulation of best practices, DEA provides actionable, *quantitative* targets for inefficient units by referencing top performers (Cook et al., 2014).

While traditional benchmarking often involves comparing firms based on strategies and best practices, DEA-based benchmarking focuses on the quantitative assessment of operational efficiency. Accordingly, this study employs DEA as a benchmarking tool, emphasizing performance efficiency rather than qualitative evaluations of managerial practices. This distinction between DEA-based benchmarking and traditional forms of benchmarking (e.g., Anderson & Peterson, 1993) is critical for understanding the methodological framework of this research.

Benchmarking is not limited to organizational or qualitative comparisons; it also encompasses quantitative performance assessments enabled by analytical models. DEA method utilized in this study not only measures the technical efficiency of DMUs but also suggests improvement strategies for inefficient units by referencing more efficient peers. Owing to these features, DEA is widely recognized in the literature as a robust tool for quantitative benchmarking (Cook, Tone, & Zhu, 2014; Emrouznejad & Yang, 2018).

In this context, the use of the term "benchmarking" in this study extends beyond its conventional meaning in the total quality management literature, and reflects an integrated, model-based benchmarking approach. Specifically, the implementation of the super-efficiency model allows for the identification of reference units, while also quantifying the necessary input reductions or output enhancements required by other units to reach the efficiency frontier. This process exemplifies a data-driven, directional benchmarking methodology rooted in core DEA literature.

In summary, the concept of benchmarking in this study specifically refers to the application of DEA for assessing and comparing firms' financial efficiency. DEA-based benchmarking enables a clear, quantitative evaluation of firms' relative performance by measuring their ability to transform inputs into outputs efficiently. Thus, while traditional benchmarking focuses on the qualitative comparison of best practices, DEA provides a structured, empirical basis for evaluating relative operational efficiency.

Data Envelopment Analysis

The first application of DEA was carried out by Charnes and colleagues in 1978 to measure the efficiency of U.S. state schools. The study was expanded when Farrell's 1957 study, "The Measurement of Productive Efficiency," caught the attention of Cooper, and the DEA technique was successfully applied for efficiency measurement. The project details were completed by Charnes and colleagues in 1981 (Cenger, 2011).

In DEA, the efficiency score is defined as the ratio of the weighted sum of outputs to the weighted sum of inputs. DMUs with an efficiency score of 1 are considered efficient, while a score below 1 indicates that the DMU is inefficient. Each DMU is assigned weights for inputs and outputs using linear programming to maximize its efficiency score. DEA not only determines the relative efficiency score of a DMU but also identifies a set of efficient units that can be used as benchmarks for improving the performance of inefficient units (Talluri, 2000).

DEA can determine the proportional changes in input-output variables relative to the efficient DMU, going beyond just comparing the efficiency score obtained by DMU with those of other DMUs. It measures the relative efficiency score of DMU either by determining the minimum possible inputs required to produce a set of outputs (input-oriented) or by determining the maximum possible outputs that can be produced from a given set of inputs (output-oriented). Additionally, it defines the production frontier or the efficiency frontier (Rahman et al., 2018).

DEA evaluates the relative efficiency of each unit through linear combinations of inputs and outputs. An inefficient unit is compared against at least one unit on the frontier, which are called peers or the reference group. However, classical DEA selects these groups solely based on mathematical optimality, which often leads to impractical or difficult-to-achieve targets. In this study, combining benchmarking with Data Envelopment Analysis identifies the closest achievable target for inefficient units, providing more realistic and implementable performance benchmarks. The method also clusters units with similar efficiency levels and comparable input-output structures, enabling meaningful benchmarking comparisons. Thus the approach improves upon traditional DEA's limitations in setting attainable targets and forming relevant comparison groups. Organizations can not only determine whether they are efficient or not, but also clearly see who to benchmark against, what criteria to use, and how to implement improvements (Ruiz, et al., 2022).

BCC Model (DEA with Variable Return Scale Assumption)

DEA, the BCC model, developed by Banker, Charnes, and Cooper (1984), extends the traditional CCR model by introducing the assumption of variable returns to scale (VRS). While the CCR model assumes proportionality between inputs and outputs, the BCC model allows for the more realistic scenario where decision-making units (DMUs) may operate under increasing, constant, or decreasing returns to scale, depending on their size and operational efficiency. This is particularly important in industries such as automotive manufacturing, where firms often face varying scale efficiencies due to high fixed costs and fluctuating market dynamics.

The BCC model provides a decomposition of efficiency into pure technical efficiency and scale efficiency. Pure technical efficiency captures a DMU's ability to optimize operations regardless of scale, while scale efficiency indicates whether the DMU is operating at an optimal size. This separation enables more precise managerial insights.

There are two principal orientations within the BCC framework: input-oriented and output-oriented. The input-oriented model seeks to minimize input consumption for a given level of output, whereas the output-oriented model aims to maximize output production without increasing inputs. In this study, the input-oriented BCC model is employed because the selected input variables (debt ratios) are cost-related. Moreover, the assumption of variable returns to scale is particularly suitable since increases in debt or investment do not guarantee proportional increases in profitability metrics in capital-intensive sectors.

In addition to measuring technical efficiency, benchmarking analysis is conducted within the BCC framework. Benchmarking involves identifying best-performing firms (efficient frontiers) and using them as reference points for inefficient firms. Through the application of the super-efficiency model, not only were efficient firms distinguished from inefficient ones, but the relative rankings among efficient firms themselves were also established, allowing for a deeper, comparative performance evaluation. This approach enhances the practical relevance of the findings, providing actionable insights for firms seeking to improve their financial performance relative to industry peers.

Thus, the BCC model's flexibility in accommodating variable returns to scale and its compatibility with benchmarking objectives make it an appropriate and effective methodological choice for the financial efficiency assessment conducted in this study.

Objective function;

$$Enk\Theta_k$$

Requirement

$$\sum_{j=1}^{N} y_{rj}\lambda_{jk} \geq y_{rk}$$

$$\Theta_k x_{ik} - \sum_{j=1}^{N} x_{ij}\lambda_{jk} \geq 0$$

$$\sum_{j=1}^{N} \lambda_j = 1$$

Super Efficiency Model

DEA models measure the efficiency of a Decision Making Unit (DMU) by limiting the efficiency index to an upper bound of "1." However, in this case, multiple DMUs may have the same efficiency score of "1," which makes it impossible to assess the relative performance superiority or inferiority between efficient DMUs. To address this issue, Andersen and Petersen (1993) proposed the Super Efficiency (SE) model, which allows for the ranking of efficient DMUs within themselves.

The DMU set is denoted by I, the input set by M, and the output set by N. For each DMU i∈I, a linear program is used to obtain its efficiency score. The formula for the Super Efficiency model is as follows:

$$Min \quad \theta_k - \varepsilon \sum_{n \in N} s_{kn}^{+} - \varepsilon \sum_{m \epsilon M} s_{km}^{-} \quad ,$$

$$\theta_k x_{km} - \sum_{i \in I, i \neq k} \lambda_i X_{im} - s_{km}^{-} = 0 \quad \forall \text{ m } \in \text{ M}$$

$$\sum_{i \in I, i \neq k} \lambda_i = 1$$

$$\lambda_i \geq 0 \qquad \forall \text{i } \in \text{I}$$

$$s_{km}^{-} \geq 0 \qquad \forall \text{m} \in \text{M}$$

$$s_{kn}^{+} \geq 0 \qquad \forall n \in \text{N}$$

$$\theta_k \geq$$

$$Min \quad \theta_k - \varepsilon \sum\nolimits_{n \in N} s_{kn}^{+} - \varepsilon \sum\nolimits_{m \epsilon M} s_{km}^{-} \quad ,$$

$$\sum_{i \in I, i \neq k} \lambda_i y_{in} - s_{kn}^{+} = Y_{kn} \qquad \forall n \in \text{N},$$

$$\theta_k x_{km} - \sum_{i \in I, i \neq k} \lambda_i X_{im} - s_{km}^{-} = 0 \quad \forall \text{ m } \in \text{ M}$$

$$\sum_{i \in I, i \neq k} \lambda_i = 1$$

$$\lambda_i \geq 0 \qquad \forall \text{i } \in \text{I}$$

$$s_{km}^{-} \geq 0 \qquad \forall \text{m} \in \text{M}$$

$$s_{kn}^{+} \geq 0 \qquad \forall n \in \text{N}$$

$$\theta_k \geq$$

Data Set

The study includes firms from the automotive sector listed on Borsa Istanbul (BIST), for which financial data could be accessed. The dataset covers companies operating in the year 2022. It is important to note that the BIST 100 index reviews company inclusion approximately every four years; therefore, the composition of firms in the automotive sector can vary across different years.

A comprehensive literature review was conducted to determine the appropriate variables for the study. Based on this review, the relevant input and output variables were selected. These variables were calculated manually using MS Excel based on the balance sheets and income statements disclosed via the Public Disclosure Platform (PDP). All calculations and data preparation steps adhered strictly to academic and methodological standards to ensure consistency and reliability.

Table 1. *Firms Under Study (Decision-Making Units)*

1	TAOSA	Tofaş Turkish Automotive Factory Inc.
2	FROTO	Ford Automotive Industry
3	KARSN	Karsan Automotive Industry and Trade Inc.
4	OTKAR	Otokar Automotive and Defense Industries Inc.
5	TTRAK	Türk Tractor and Agricultural Machinery Inc.
6	ASUZU	Anadolu Isuzu Automotive Industry and Trade Inc.
7	TMSN	Tumasan Engine and Tractor Trading Inc.
8	DOAS	Dogus Automotive Service and Trade Inc.

The primary reason for selecting publicly listed companies in the automotive sector traded on Borsa Istanbul is the transparency, accessibility, and standardized presentation of their financial data. These firms are subject to regular financial reporting and independent auditing in accordance with the regulations of the Capital Markets Board of Turkey (SPK).

Table 2. *Input-Output Variables Used in the Study*

	Input Variable		*Output Variable*
1	Total Debt/Total Assets (X1)	1	Net profit/Sales (Y1)
2	Net Debt / EBITDA (X2)	2	Net profit/Total Assets (Y2)
		3	Net profit/Equity (Y3)

A company can finance its investments with debt and/or equity. The ratio of a company's debt to equity is defined as financial leverage or gearing (Pandey, 2010).

Therefore, in this study, the leverage ratio, which is a cost factor for companies, is used as an input variable, along with the Net Debt/EBITDA ratio, which shows how many times a company's net debt (*Short-term borrowings + the short-term portion of long-term borrowings + long-term borrowings-Cash and Cash Equivalents - Short-Term Financial Investments*) is of the annual EBITDA (Net Operating Profit + Depreciation + Amortization Expenses).

Profitability performance indicators measure a company's efficiency and success. Typical indicators of a company's profitability measures include Return on Equity (ROE) and Return on Assets (ROA); additionally, Return on Sales (ROS) can also be used. Therefore, the output variables are selected from these profitability ratios.

In DEA (Data Envelopment Analysis), the number of Decision-Making Units (DMUs) to be analyzed is determined based on the number of input and output variables included in the model. There are two widely accepted rules in the literature regarding this issue. The first rule suggests that the number of DMUs (n) should be at least three times the total number of inputs (m) and outputs (s), i.e., n≥3(m+s)n \geq 3(m + s)n≥3(m+s) (Vassiloglou & Giokas, 1990). The second rule states that for a reliable analysis, the number of DMUs should be at least equal to the total number of inputs and outputs plus one, i.e., n≥m+s+1n \geq m + s + 1n≥m+s+1 (Dyson et al., 2001, pp. 254–259). This study follows these recommendations by ensuring the sample size is close to or within acceptable limits, while also acknowledging this aspect as a limitation to be addressed in future studies through a larger sample.

Table 3. *Research Variables (2022)*

	(X1)	*(X2)*	*(Y1)*	*(Y2)*	*(Y3)*
TAOSA	0,72	-0,44	13,06	28,82	100,39
FROTO	0,78	1,41	10,83	26,81	117,99
KARSN	0,71	6,27	4,26	2,5	9,1
OTKAR	0,85	4,68	12,9	12,3	68,85
TTRAK	0,74	-0,28	13,61	29,85	104,44
ASUZU	0,59	0,29	9,85	10,34	25,82
TMSN	0,51	-0,13	15,52	21,68	43,98
DOAS	0,43	-0,36	16,73	51,44	97,68

Table 4. *Distribution of Variables Used in Technical Efficiency Measurement*

İnput	***Average***	***Standard Deviation***
Total Debt/Total Assets (X1)	0,66625	0,142922307
Net Debt / EBITDA (X2)	1,43	2,60073616
Output		
Net profit/Sales (Y1)	12,095	3,875118431
Net profit/Total Asset (Y2)	22,9675	15,122803
Net profit/Equity (Y3)	71,03125	40,548781

Distribution of Variables n=8	
The average efficiency score for the entire sample	0,5
The standard deviation of the average efficiency score for the entire sample	0,835425
Maksimum	1
Minimum	0,5059
The number of efficient companies	4
The number of inefficient companies	4

When examining the statistical distribution of the variables used in the study, it is observed that the input variables, Total Debt/Total Assets (X1) and Net Debt/EBITDA (X2), show varying degrees of dispersion. The mean value of the X1 variable is 0.666 with a standard deviation of 0.142, indicating a relatively homogeneous distribution among the firms. This suggests that the financial structure in terms of debt-to-assets is similar across the sector.

In contrast, the X2 variable, representing Net Debt/EBITDA, has a mean of 1.43 with a notably high standard deviation of 2.60. This high variance reveals significant differences in the firms' debt repayment capacities, with some companies carrying a substantially heavier debt burden relative to their operating profits. From a DEA perspective, such variability enhances the model's discriminatory power, facilitating a clearer separation between efficient and inefficient decision-making units.

Regarding the output variables, Net profit/Sales (Y1), Net profit/Total Assets (Y2), and Net profit/Equity (Y3) represent different aspects of firm profitability. The mean of Y1 is 12.09% with a standard deviation of 3.87, indicating moderate variability in profitability relative to sales. Y2 (ROA) has a higher mean of 22.96% and a standard deviation of 15.12, reflecting greater dispersion in asset efficiency among firms. Y3 (ROE) shows an even higher mean of 71.03% with a standard deviation of 40.54, suggesting significant performance differences in returns on equity. This high dispersion in output variables is advantageous for DEA, as it strengthens the model's ability to differentiate between decision-making units.

Table 5. *Pearson Correlation Matrix of Leverage (X1-X2) and Profitability (Y1-Y3) Variables in the Automotive Sector*

	X1 (TD/TA)	***X2 (Net Debt/EBITDA)***	***Y1 (NP/Sales)***	***Y2 (NP/TA)***	***Y3 (NP/Equity)***
X1	1.000	-0.239	-0.216	-0.492	-0.347
X2	-0.239	1.000	**-0.726**	-0.520	-0.462
Y1	-0.216	**-0.726**	1.000	0.704	0.788
Y2	-0.492	-0.520	0.704	1.000	**0.906**
Y3	-0.347	-0.462	0.788	**0.906**	1.000

(NP = Net Profit; TA = Total Assets. Significant correlations are marked in bold (two-tailed test): X2-Y1 ($r = -0.726$, $p < .001$), Y2-Y3 ($r = 0.906$, $p < .001$).

When Table 5 is examined, the correlation analysis offers significant insights into the relationship between financial structure and profitability of firms in the automotive sector. In particular, the strong negative correlation (r = -0.726) between the Net Debt/EBITDA ratio (X2) and Net Profit/Sales (Y1) indicates that leverage exerts substantial pressure on operational profitability. Combined with the sector's high fixed cost structure, this suggests that debt financing is often an inevitable choice, although excessive indebtedness may adversely affect profitability. Indeed, firms with high X2 values (KARSN) tend to exhibit low Y1 values, whereas some firms (FROTO) manage to enhance equity efficiency through strategic use of debt.

The high correlation (r = 0.906) between Net Profit/Total Assets (Y2) and Net Profit/Equity (Y3) reflects the inherent similarity between these two profitability indicators, as return on equity is fundamentally composed of asset profitability and the effect of financial leverage. The simultaneous use of both indicators does not undermine the validity of the Data Envelopment Analysis (DEA), as the model accommodates multiple outputs regardless of their statistical collinearity. This allows for a comprehensive evaluation of operational efficiency in conjunction with financial structure (Zhou et al., 2018).

DEA does not rely on correlation coefficients when assessing efficiency, as it evaluates firms based on input-output optimization rather than linear dependencies**.** Even if two variables (Y2 and Y3) exhibit a high correlation (r = 0.906), DEA treats them as distinct performance measures and ensures that multicollinearity does not distort efficiency scores.

Furthermore, DEA assesses firms relative to an efficient frontier where long-term debt is viewed not as inefficiency but as a contributor to optimal resource allocation, thereby addressing sector-specific constraints (e.g., high fixed costs, large-scale production). While correlation analysis highlights statistical trends, DEA provides a more nuanced efficiency assessment by incorporating multiple inputs and outputs without requiring statistical dependency.

The moderate negative correlations between Total Debt/Total Assets (X1) and both Y2 and Y3 suggest that the nature of debt (e.g., maturity structure, cost) plays a more decisive role in profitability than the overall leverage ratio. This aligns with the finding that the Net Debt/EBITDA ratio (X2) has a stronger relationship with Y1, emphasizing that in the automotive sector, not only the amount but also the financial burden and management of debt must be considered.

Finally, when DEA scores are interpreted alongside correlation results, it becomes evident that firms with high equity profitability (FROTO, TTRAK) utilize debt strategically to achieve efficiency. This supports capital structure theories by showing that leverage may have a positive impact on firm value (Myers, 2001). Additionally, considering the unique structure of the sector particularly capital intensity and scale of production long-term debt is interpreted within the DEA model as optimal capital use rather than inefficiency. As such, DEA offers a flexible and explanatory framework that reflects sectoral realities.

Therefore, the non-parametric nature of DEA enables it to assess performance reliably and flexibly even in datasets with high correlation among variables; this represents a critical advantage for researchers aiming to overcome the limitations of traditional regression or correlation-based methods.

Table 6. *Regression Analysis Results: The Impact of Leverage Ratios on Profitability Metrics in the Automotive Sector*

Bağımsız Değişken	*Bağımlı Değişken*	*Etki Durumu*	*Açıklama*
X1	Y1	Anlamlı (p<0.05)	Borç/Aktif oranı düştükçe Net Kar/Satış oranı artıyor.
X1	Y2	Anlamlı (p<0.05)	Borç/Aktif oranı arttıkça ROA düşüyor.
X1	Y3	Anlamlı (p<0.05)	ROE üzerinde de negatif anlamlı etkisi var.
X2	Y1	Anlamlı (p<0.05)	Net Borç/EBITDA arttıkça Net Kar/Satış oranı düşüyor.
X2	Y2	Anlamlı (p<0.05)	Aynı şekilde ROA'da düşüş görülüyor.
X2	Y3	Anlamlı (p<0.05)	ROE de Net Borç/EBITDA'dan negatif etkileniyor.

(Tüm ilişkiler *p* < .05 düzeyinde istatistiksel olarak anlamlıdır (X2-Y3 için *p* = .001)

Tablo 6 The regression analyses conducted to evaluate the impact of leverage ratios on profitability indicators reveal that both X1 (Total Debt/Total Assets) and X2 (Net Debt/EBITDA) have a statistically significant and negative effect on profitability ratios, including Net Profit/Sales (Y1), Return on Assets (Y2), and Return on Equity (Y3). In particular, the X1 variable demonstrates stronger explanatory power across all profitability indicators in terms of statistical significance. This finding indicates that high levels of leverage suppress firms' profitability performance and create adverse effects on financial efficiency.

Similarly, the Net Debt/EBITDA ratio also exhibits a negative relationship with profitability, highlighting the fragile link between a firm's operating profitability and its debt servicing capacity. The results statistically confirm the relationship between financial structure and performance, underlining the negative impact of leverage on profitability. In this context, the findings obtained through the DEA model in the study are consistent with the regression results, reinforcing the robustness of the conclusions.

Empirical Results

In this study, which uses data from the year 2022, the BCC model based on input-oriented and scale-dependent variable return assumptions was applied because companies have higher control over inputs and a unit change in inputs does not cause a proportional change in outputs. The BCC model used in the analysis shows how much the inputs should be reduced while keeping outputs constant. The target relative efficiency value for the companies is 1.00. Companies achieve technical efficiency by providing maximum output per input used. Firms that do not reach this value are considered 'inefficient.'

Table 7. *2022 Year Variable Return to Scale Radial Input-Oriented Efficiency Scores*

DMU	*Skor*	*X1*	*X2*	*Y1*	*Y2*	*Y3*	*Benchmarking*	*X1*	*X2*	*Y1*	*Y2*	*Y3*
TAOSA	1	92,87	91,87	0	0	1	0					
FROTO	1	0,99	0,01	0	0	1	0					
KARSN	0,6056	1	0	0,79	0,1	0,11	8 (1,00)	0	4,16	12,47	48,94	88,58
OTKAR	0,5059	1	0	0,99	0	0,01	8 (1,00)	0	2,73	3,83	39,14	28,83
TTRAK	1	84,28	83,28	0,08	0	0,92	0					
ASUZU	0,7288	1	0	0,83	0,12	0,05	8 (1,00)	0	0,57	6,88	41,1	71,86
TMSN	0,8431	1	0	0,94	0,03	0,03	8 (1,00)	0	0,25	1,21	29,76	53,7
DOAS	1	1,01	-0,01	0	1	0						

According to the results of the BCC input-oriented model (Table 5), among the 8 companies listed in Table 7, 4 firms (TAOSA, FROTO, TTRAK, DOAS) were identified as relatively efficient, each achieving a full efficiency score of 1.000 (100%), while the remaining 4 firms (KARSN, OTKAR, ASUZU, TMSN) were found to be relatively inefficient. The average efficiency score for all companies was calculated as 0.50. The deviation levels from the efficiency frontier for inefficient firms were as follows: OTKAR with 50.59%, KARSN with 60.56%, ASUZU with 72.88%, and TMSN with 84.31%. These deviation percentages indicate the extent to which each inefficient firm would need to reduce input usage to reach the efficiency level of the benchmark companies.

Table 8. *2022 Scale-Dependent Variable Return Radial Input-Oriented Super Efficiency Scores*

DMU	*Skor*	*X1*	*X2*	*Y1*	*Y2*	*Y3*	*Benchmarking*	*X1*	*X2*	*Y1*	*Y2*	*Y3*
TAOSA	big	43,18	42,18	0	0	20,61	0					
FROTO	big	0,99	0,01	0,13	0,05	76,24	0					
KARSN	0,6056	1	0	0	0	0	8 (1,00)	0	4,16	12,47	48,94	88,58
OTKAR	0,5059	1	0	0	0	0	8 (1,00)	0	2,73	3,83	39,14	28,83
TTRAK	big	84,28	83,28	42,87	4,64	77,04	0					
ASUZU	0,7288	1	0	0	0	0	8 (1,00)	0	0,57	6,88	41,1	71,86
TMSN	0,8431	1	0	0	0	0	8 (1,00)	0	0,25	1,21	29,76	53,7
DOAS	big	1,01	-0,01	8,06	5,98	0,23	0					

To rank the relatively efficient companies, a super-efficiency ranking was calculated based on the 2022 data (Table 8). However, since the efficiency levels of the efficient firms are at their maximum, it was not possible to identify the most efficient firm within the group of efficient companies. When looking at potential improvement recommendations for the relatively inefficient firms, all of them took DOAS as the reference, the company closest to them. This shows that the least efficient company among the relatively efficient ones is DOAS. In this context, under the scale-dependent variable return assumption, technical efficiency values of automotive sector companies were measured by comparing them with reference firms, and recommendations were made based on these values. The technical inefficiency of firms is defined by the difficulty in reaching the targeted output levels, which is typically associated with excessive input (usually cost) usage.

In the super-efficiency model, the scores calculated for TAOSA, FROTO, and TTRAK were reported as 'big'. This indicates that the efficiency scores of these companies are mathematically considered infinite (∞), signifying their absolute leadership position within the sector.

Table.8. *DEA-Based Benchmarking Results for 2022*

DMU	*Score*	*Benchmarking*	*Explanation*
TAOSA	big	–	High input level but also a very high output (20.61). According to the super-efficiency model, it is significantly more productive than the others.
FROTO	big	–	Technically efficient, but not primary. Could likely become efficient with a slight input reduction.
KARSN	0.6056	8 (1.00)	Rather low score. Its benchmark, DOAS (DMU 8), performs significantly better.
OTKAR	0.5059	8 (1.00)	Similarly, the reference unit DOAS has much stronger performance. Very low efficiency score.
TTRAK	big	–	Super-efficient. Has high output levels. Potentially one of the "stars" of this model.
ASUZU	0.7288	8 (1.00)	Not efficient but at a moderate level. DOAS is again the benchmark.
TMSN	0.8431	8 (1.00)	Relatively more efficient but still below the ideal. DOAS remains the reference unit.
DOAS	big	–	Super-efficient, but note the slightly negative input (X2: -0.01), which, while not affecting efficiency scores, should be verified.

According to Table 9 results; for potential improvement, the relatively inefficient firms OTKAR, KARSN, ASUZU, and TMSN can achieve 100% efficiency by emulating the efficient firm DOAS, with which they share 100% similarity. Meanwhile, TTRAK demonstrates a super-efficient performance with its high outputs, standing out in the sector. This implies that other units can learn from TTRAK's performance strategies.

The fact that DOAS ranks at the lowest tier among efficient units leads us to define it as "marginally efficient" in technical terms meaning that it produces the maximum output possible given its current inputs, yet operates at a lower performance level compared to other efficient units. At the same time, it serves as a reference point for inefficient units. Although reaching a high-performance level like TAOSA would require an output increase of 50 to 88 times which is practically unfeasible achieving the DOAS level is possible through a 4 to 12 fold improvement, which can be attained via gradual optimizations while maintaining the current operational structure. This positions DOAS as a more realistic "role model" in terms of managerial goal-setting, whereas units like TAOSA and FROTO should be adopted as long-term transformation targets. For immediate improvements, it would be beneficial to examine and take inspiration from DOAS's input utilization strategies, output optimization techniques, and scale management model. In conclusion, DOAS should be considered as the "minimum efficiency threshold," and TAOSA as the "excellence level"; firms should initially aim to reach the DOAS level and then strive toward achieving TAOSA.

All inefficient DMUs fully utilize the X1 (Total Debt/Total Assets) input at maximum capacity (X1=1), yet exhibit idle capacity in the X2 (Net Debt/EBITDA) input (X2=0). Output analysis reveals that inefficient units show particularly significant deficiencies in Y3 (Net Profit/Equity) performance, with values ranging between 0.01 and 0.11, in stark contrast to the 0.92–1 range observed in efficient units. Additionally, the Y2 (Net Profit/Total Assets) output also emerges as a problematic indicator for most units. Based on these findings, the recommended improvement steps are as follows:

Priority Action: Enhancing the critically low Net Profit/Equity (Y3) ratio in inefficient units.

Resource Optimization: Reallocating resources from the underutilized Net Debt/EBITDA (X2) input to the fully utilized Total Debt/Total Assets (X1) domain.

Best Practice Transfer: Adopting the operational model of DOAS, the only unit demonstrating success in the Y2 (Net Profit/Total Assets) output.

The actions required for inefficient firms are as follows:

KARSN must reduce its Net Debt/EBITDA ratio by 4.16%, despite not needing to change its leverage ratio. It also needs to increase its return on sales by 12.47%, return on assets by 48.94%, and return on equity by 88.58%. This suggests that the firm is struggling to meet the high cost of debt, which is reflected in its return on equity due to the financial leverage effect.

OTKAR must reduce its Net Debt/EBITDA ratio by 2.73%, increase its return on sales by 3.83%, return on assets by 39.14%, and return on equity by 28.83% to achieve 100% efficiency.

ASUZU must reduce its Net Debt/EBITDA ratio by 0.57%, increase its return on sales by 6.88%, return on assets by 41.10%, and return on equity by 71.86% to reach 100% efficiency and resemble DOAS. Lastly, TMSN must reduce its Net Debt/EBITDA ratio by 0.25%, increase its return on sales by 1.21%, return on assets by 2976%, and return on equity by 53.70% to achieve 100% efficiency. These results show that if the firm reduces its inputs by the specified rates, it will experience a corresponding increase in outputs.

Conclusion and Recommendations

This study was conducted to evaluate the financial performance of eight companies operating in the automotive sector and listed on Borsa Istanbul for the year 2022. Financial data were obtained from the Public Disclosure Platform (KAP). A super-efficiency-based benchmarking approach was adopted by employing the input-oriented variable returns to scale (BCC) model of Data Envelopment Analysis (DEA), which is rooted in the broader framework of Decision Analysis (DA). In the model, Net Sales, Return on Equity (ROE), and Net Profit were used as output variables, while Total Assets, Cost of Goods Sold (COGS), Short-Term Liabilities, and Long-Term Liabilities were considered as input variables. In this way, the relationship between input efficiency and financial outcomes was analyzed in a multidimensional manner.

Findings from the DEA revealed that firms with relatively low efficiency scores (OTKAR 50.59%; KARSN 60.56%; ASUZU 72.88%; TMSN 84.31%) had significantly high Net Debt/EBITDA ratios. These high ratios were found to negatively affect financial performance indicators such as ROE, indicating that inefficient firms struggle to generate sufficient returns on borrowed capital. This suggests that financial leverage does not translate into value creation under current cash flow constraints.

Among the firms ranked by super-efficiency scores, TTRAK stood out. Although DOAS was frequently used as a reference firm, TTRAK demonstrated superior output production using the same level of inputs, positioning it as the “star performer” in terms of absolute performance. This highlights DEA’s strength not only in relative benchmarking but also in assessing raw productivity. Considering the high fixed-cost structure and scale-based production processes of the sector, borrowing appears to be a necessary financing tool. However, rather than the absolute amount of debt, its cost and impact on cash flows are more decisive. These findings underline that DEA, though a classical method, still offers valuable insights for contemporary performance evaluations.

By combining both parametric methods (regression and correlation analysis) and the non-parametric DEA approach, this study evaluated the relationship between leverage and profitability from a multidimensional perspective. The strong negative correlation between the Net Debt/EBITDA ratio and profitability indicators (e.g., $r = -0.726$ between Net Debt/EBITDA and Net Profit Margin) statistically confirms that debt pressure suppresses efficiency, thus reinforcing the inefficiency results obtained through DEA. Moreover, since DEA is not affected by multicollinearity, high correlations among variables do not compromise the model's validity. This coherence between methods strengthens the credibility of the study's findings.

From a methodological standpoint, the analysis was based on financial data from a single year and a relatively limited sample, which may restrict the generalizability of the results. Furthermore, the exclusion of external macroeconomic variables such as exchange rates and inflation especially relevant in a volatile economy like Turkey limits the external validity of the model. To overcome these limitations, future studies should consider multi-year data, robustness tests with alternative variables, and hybrid models incorporating macroeconomic indicators.

Future research could expand the analysis to compare Turkish automotive firms with global competitors to assess performance on an international scale. Additionally, integrating qualitative data through expert interviews would provide deeper insight into structural dynamics. Dynamic DEA models such as panel DEA, the Malmquist Index, or window analysis could also be employed to track performance changes over time, offering strategic guidance for continuous improvement.

In conclusion, this study does not merely offer an absolute efficiency evaluation but proposes a strategic benchmarking framework that encourages continuous improvement. Even efficient firms may experience fluctuations in performance over time, and periodic benchmarking can help maintain long-term competitiveness. In this context, DEA serves not only as a tool for technical efficiency assessment but also as a mechanism for evaluating a firm's adaptability to sectoral competition.

Ethical Declaration

During the writing process of the study "*Financial Performance Analysis of Borsa Istanbul-Listed Automotive Firms: A DEA and Benchmarking Approach*" scientific rules, ethical and citation rules were followed. No falsification was made on the collected data and this study was not sent to any other academic publication medium for evaluation.

Etik Beyan

"*Borsa İstanbul'da İşlem Gören Otomotiv Firmalarının Finansal Performansının VZA ve Benchmarking ile Değerlendirilmesi* " başlıklı çalışmanın yazım sürecinde bilimsel kurallara, etik ve alıntı kurallarına uyulmuş; toplanan veriler üzerinde herhangi bir tahrifat yapılmamış ve bu çalışma herhangi başka bir akademik yayın ortamına değerlendirme için gönderilmemiştir.

Declaration of Conflict

There is no potential conflict of interest in the study.

Çatışma Beyanı

Çalışmada herhangi bir potansiyel çıkar çatışması söz konusu değildir.

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GENİŞLETİLMİŞ ÖZET

Performans ölçümü, şirketlerin verimliliğini ve etkinliğini izlemek amacı güderken, finansal göstergeler kurumsal performans analizi için yaygın araçlardır. Veri Zarflama Analizi (VZA), firmaların performanslarını ölçmek, karşılaştırmak ve sıralamak için kullanılmaktadır. Bu çalışma, otomotive sektöründe yer alan firmaların VZA yoluyla, etkili borç yönetimine sahip firmalar ile bu özelliğe sahip olmayan firmaların finansal performanslarını karşılaştırmalı olarak analiz etmek, birbiri ile kıyaslayarak, bu konuda verimli olmayan firmaların daha verimli olması için önerilerde bulunmaktır. Çalışma, firmaların finansal sürdürülebilirliklerini artırmak için stratejiler geliştirmeyi amaçlamaktadır. VZA yöntemi; benzer işleri yapan çoklu girdi/çıktıya sahip organizasyonel birimlerin göreli etkinliklerini ölçmede kullanılan matematiksel programlama tabanlı bir yöntemdir. Özellikle birden çok girdi ya da çıktının ağırlıklı girdi veya çıktı kümesine dönüştürülemediği durumlarda VZA etkin bir yaklaşım olarak kabul edilmiştir. Bu bağlamda çalışmada; Borsa İstanbul'da işlem gören otomotive sektörüne ait firmaların 2022 yılına ait görece finansal performansları VZA yöntemiyle ölçülmüştür. Bu uygulamada girdi/çıktı bileşimlerinde yapılacak değişiklikler oransal olarak belirtilmiştir. Girdi ve çıktı değişkenleri kamu aydınlatma platformundan (KAP) elde edilen mali tablolar yardımı ile MS EXCEL'de hesaplanmıştır. Bir firma yatırımlarını borç ve/veya öz sermaye ile finanse edebilir. Firmanın borçlarının öz kaynaklara oranı, finansal kaldıraç veya dişli olarak tanımlanır (Pandey, 2010). Bu nedenle çalışmada girdi değişkeni olarak firmalar için maliyet unsuru olan kaldıraç oranı ve bir firmanın net borcunun (Kısa vadeli borçlanma +uzun vadeli borçlanmanın kısa vadeli kısmı + uzun vadeli borçlanma- Nakit ve Nakit Benzerleri- Kısa vadeli Finansal Yatırımlar), yıllık yarattığı FAVÖK'ın (Net Faaliyet Karı + Amortisman + İtfa Giderleri) kaç katı olduğunu gösteren Net Borç/FAVÖK oranı kullanılmıştır. Kârlılık performans göstergeleri, bir şirketin etkinliğini ve başarısını ölçer. Firmanın kârlılık ölçütlerinin tipik göstergeleri olarak, öz sermaye getirisi (ROE) ve aktif getirisidir (ROA); ayrıca satışların getirisi (ROS) de kullanılabilir. Bu nedenle çıktı değişkenleri de bu karlılık oranlarından seçilmiştir. Literatür incelendiğinde yapılan çalışmaların çoğunda VZAyöntemi kullanılmış olup, bu çalışmalarda yalnızca etkin ve daha az etkin olan karar verme birimleri (KVB) belirlenmiştir. Ancak, görece verimsiz firmaların nasıl verimli hale gelebileceğine dair girdi ve çıktı değişkenlerinde yapılması gereken değişimler üzerine yeterli bilgi verilmemiştir. VZA yöntemini etkin bir kıyaslama aracı olarak kullanan çalışmalar da sınırlı kalmıştır ve bu yöntem farklı endüstrilerde, örneğin telekomünikasyon, bankacılık ve otelcilik alanlarında daha fazla kullanılmıştır. Özellikle, araştırmaların otomotive sektöründe yaygın olmaması, bu sektörde VZA'nın önemini artırmaktadır. Çalışmada otomotive sektörüne odaklanmanın diğer nedeni, bu sektörün sabit varlıklar açısından yüksek miktarlara sahip olması ve yüksek kaldıraç oranları sunmasıdır. Çalışmanın literatüre katkısı düşünüldüğünde; otomotive sektöründeki verimli birimler için bir ölçüt sunarak, rekabet gücü ve sürekli verimlilik için referans oluşturmayı hedeflemektedir. VZA ile, performanslarında gelişme göstermeyen verimsiz birimlerin, verimli birimlerin referans alınarak etkinlik düzeyine ulaşmalarına yardımcı olacak iyileştirme önerileri sunulacaktır. Elde edilen bulgulara göre, görece verimsiz firmalar arasında sırasıyla OTKAR (%50,59), KARSN (%60,56), ASUZU (%72,88) ve TMSN (%84,31) firmaları yer almıştır. Yüksek Net Borç/FAVÖK oranlarının, bu firmaların verimlilik sıralamalarını etkilediği ve mali sağlıklarında düşüşe yol açtığı gözlemlenmiştir. Çalışmada, görece verimsiz firmalara kaldıraç oranını azaltma önerisi verilmemiştir; bunun yerine, nakit akışları ve borcun maliyetinin daha belirleyici olduğu sonucuna varılmıştır. %100 etkinliğe ulaşan firmalar ise TAOSO, FROTO, TTRAK ve DOAS olarak belirlenmiştir. Verimli firmalar arasında süper etkinlik sıralaması yapılmış, ancak verimlilik düzeylerinin en üst seviyede olması nedeniyle en verimli firmanın tespiti sağlanamamıştır. Görece verimsiz firmalar, kendilerine en yakın DOAS firmasını referans almış ve etkin olmayan firmalara en yakın referans DOAS firması gösterilmiş ve kıyaslanmıştır. Yapılan analizlerde parametrik yöntemler (regresyon ve korelasyon analizi) ile parametrik olmayan VZA (Veri Zarflama Analizi) yaklaşımının birlikte kullanılması sayesinde, kaldıraç ve kârlılık arasındaki ilişki çok boyutlu bir bakış açısıyla değerlendirilmiştir. Net Borç/FAVÖK oranı ile kârlılık göstergeleri arasındaki güçlü negatif korelasyon (örneğin Net Borç/FAVÖK ile Net Kâr Marjı arasında r = -0,726), borç baskısının etkinliği azalttığını istatistiksel olarak teyit etmektedir. Bu bulgu, VZA ile elde edilen verimsizlik sonuçlarını da güçlendirmektedir. Ayrıca, VZA yöntemi değişkenler arası çoklu doğrusal bağlantıdan (multicollinearity) etkilenmediği için, değişkenler arasındaki yüksek korelasyonlar modelin geçerliliğini zedelememektedir. Bu iki yöntemin sonuçlarındaki uyum, çalışmanın bulgularının güvenilirliğini artırmaktadır. Araştırma, sürekli iyileştirmenin önemini vurgulamakta ve firmaların düzenli olarak VZA metodunu kullanarak durum analizi yapmalarını önermektedir. Çalışmanın hassasiyetine değinmek gerekirse, VZA sonuçlarının yorumlanırken dikkat edilmesi gereken unsurlar arasında girdi ve çıktılar yer almaktadır. Gelecek çalışmalarda, VZA metodunun KVB sayısı artırılarak birden fazla yıl boyunca karşılaştırmalar yapılması ve farklı girdi/çıktı değişkenleri kullanılması önerilmektedir.