

## Evaluation and Ranking of Companies in the Transportation and Infrastructure Sector Using Data Envelopment Analysis (DEA)

Maliheh. Amini Pozveh<sup>1</sup>  Mohammad. Khodabakhshi<sup>2\*</sup>  Seyyed Javad. Ghanefar<sup>3</sup> 

<sup>1</sup> PhD Candidate in Applied Mathematics, Department of Applied Mathematics, Faculty of Mathematical Sciences, Shahid Beheshti University, Tehran, Iran

<sup>2</sup> Professor, Department of Industrial and Applied Mathematics, Faculty of Mathematical Sciences, Shahid Beheshti University, Tehran, Iran.

<sup>3</sup> Head of the Office of Consultants and Contractors, Plan and Budget Organization of Iran.

\* Corresponding author email address: m\_khodabakhshi@sbu.ac.ir

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### ABSTRACT

Transportation infrastructure plays a vital role in economic development, necessitating rigorous and reliable methods for evaluating contractor performance. Traditional administrative classification systems may not fully capture differences in the relative operational efficiency of firms. This study employs the output-oriented Andersen–Petersen (AP) super-efficiency model within the Data Envelopment Analysis (DEA) framework to evaluate and rank 30 road and transportation contractors using financial, operational, contract-related, and managerial indicators. To examine the consistency between DEA-based rankings and the established four-tier administrative classification system, Spearman's rank correlation coefficient is calculated. The results indicate a strong and statistically significant positive correlation between the two ranking systems ( $\rho = 0.927$ ,  $p < 0.001$ ), suggesting substantial overall alignment between quantitative efficiency rankings and administrative classifications. Nevertheless, firm-level comparisons reveal notable differences between relative efficiency and administrative status. For instance, company B2 ranks first in DEA-based efficiency despite being assigned to Tier 2 in the administrative classification system. This discrepancy highlights the possibility that administrative classifications may fail to identify certain firms demonstrating comparatively high efficiency under the selected DEA framework. The findings suggest that DEA-based benchmarking could complement existing administrative classification systems by providing additional quantitative evidence for contractor evaluation, selection, and performance monitoring. By integrating relative efficiency assessment with established administrative criteria, the proposed approach offers a systematic basis for improving transparency and evidence-based contractor evaluation in transportation infrastructure projects.

**Keywords:** *Data Envelopment Analysis, Performance Evaluation, Company Ranking, Transportation, Road Sector, Construction Projects, Infrastructure Projects.*

## Introduction

Transportation infrastructure is widely recognized as a fundamental component of countries' economic, social, and spatial development. Roads, railways, ports, airports, and other transportation networks constitute the backbone of a nation's domestic and international connectivity, playing a crucial role in enhancing productivity, reducing transaction costs, expanding markets, and promoting industrial growth (Ziyari et al., 2016). Furthermore, transportation infrastructure contributes to reducing regional inequalities, facilitating access to public services, and improving citizens' quality of life. Countries that have achieved significant economic progress have consistently pursued targeted, long-term investments in this sector to promote sustainable economic and social development through infrastructure improvement (Ghanbari et al., 2024).

Companies operating in the road construction and transportation sectors play a pivotal role in infrastructure development by translating government policies and development programs into practical outcomes. Through the construction, maintenance, and upgrading of roads and transportation networks, these companies contribute not only to the physical development of a country but also to job creation, the enhancement of national technical capabilities, the development of industrial and engineering capacities, and the efficient utilization of national resources. The effective performance of these companies is essential for ensuring the efficient use of public infrastructure budgets and the timely completion of infrastructure projects. Conversely, poor performance or mismanagement in this sector may lead to project delays, resource wastage, public dissatisfaction, and safety risks (Ghasemi, 2025).

Despite the importance of evaluating companies operating in the road construction and transportation sectors, systematic studies based on actual operational data that assess their relative efficiency within a rigorous, multidimensional analytical framework remain limited in the national research context. Existing evaluation practices have largely focused on qualitative ranking systems and qualification assessments, which are generally descriptive or administrative in nature or rely primarily on companies' previous performance records. However, the application of rigorous analytical methods that utilize actual operational data can provide a more accurate and comprehensive assessment of companies' relative efficiency, strengths, and weaknesses. Such assessments can contribute significantly to improving project management systems and supporting more informed decision-making in infrastructure development.

To address this research gap, the present study employs Data Envelopment Analysis (DEA) and the Andersen–Petersen (AP) super-efficiency model to evaluate the performance of 30 companies operating in the road construction and transportation sectors. Specifically, the study aims to provide a systematic, data-driven framework for ranking and comparing these companies in terms of their

relative efficiency, thereby contributing to the improvement of performance evaluation practices in the infrastructure sector.

The following section describes the research methodology in detail, including the selection of evaluation indicators, the specification of the DEA model, and the procedures used to calculate super-efficiency scores.

## **1. Research Methodology**

This section presents the methodological approach adopted to evaluate the relative performance of companies operating in the road construction and transportation sectors. Given the multidimensional nature of performance assessment in these sectors, conventional evaluation approaches, including descriptive analyses and qualitative ranking methods, may not fully capture differences in the relative performance of companies. Accordingly, this study employs Data Envelopment Analysis (DEA), a non-parametric technique based on mathematical programming, to assess and compare the relative performance of the selected companies based on the specified indicators.

The remainder of this section is organized as follows. First, the theoretical foundations of DEA and its principal models are introduced. Next, the output-oriented Andersen–Petersen (AP) super-efficiency model implemented in this study is described. The evaluation indicators used in the analysis are then presented, followed by the statistical validation procedure based on Spearman’s rank correlation coefficient, which is used to examine the association between the DEA-based rankings and the administrative tiers of the contractors.

### **1.1. Data Envelopment Analysis**

Data Envelopment Analysis (DEA) is a non-parametric method based on mathematical programming that is used to evaluate the relative efficiency of decision-making units (DMUs). The theoretical foundations of DEA can be traced to Farrell (1957), who introduced a framework for measuring productive efficiency based on the relationship between inputs consumed and outputs produced. Although this approach provided an important foundation for efficiency measurement, a more comprehensive framework was required to evaluate units involving multiple inputs and outputs simultaneously. In this context, Charnes, Cooper, and Rhodes (1978) introduced the CCR model, establishing DEA as a mathematical programming approach for evaluating relative efficiency without requiring the specification of a parametric production function or the assignment of input and output weights in advance (Charnes et al., 1978).

Under DEA, the performance of each DMU is evaluated relative to the performance of other units within the same reference set. Accordingly, the efficiency frontier is constructed from the best observed practices in the dataset, and units located on this frontier are considered efficient, whereas

units operating below it are classified as inefficient relative to the observed frontier. The main advantages of DEA include its ability to accommodate multiple inputs and outputs simultaneously, eliminate the need to specify weights in advance, identify reference units, and establish potential improvement targets for inefficient units. These characteristics have contributed to the widespread application of DEA in various fields, including manufacturing, energy, transportation, banking, and public services (Mehregan, 2004).

Two fundamental and widely used DEA models are the Charnes–Cooper–Rhodes (CCR) model and the Banker–Charnes–Cooper (BCC) model. The CCR model assumes constant returns to scale (CRS) and measures the overall technical efficiency of DMUs. In contrast, the BCC model, developed by Banker et al. (1984), incorporates the assumption of variable returns to scale (VRS). This model enables the assessment of pure technical efficiency and allows it to be distinguished from scale effects. The choice between these models depends on the characteristics of the units under investigation and the assumptions concerning the relationship between inputs and outputs (Banker et al., 1984).

DEA models can also be formulated using either an input-oriented or an output-oriented approach. The input-oriented approach aims to minimize input consumption while maintaining the current level of outputs. Conversely, the output-oriented approach seeks to maximize output levels while keeping input quantities unchanged. The choice between these orientations depends on the objectives of the study, the nature of the decision-making problem, and the extent to which DMUs can control their inputs and outputs. Therefore, selecting an appropriate DEA model requires consideration of both the returns-to-scale assumption and the orientation of the model.

As the application of DEA expanded, one important issue attracting researchers' attention was the limited ability of conventional models to rank efficient DMUs. Under the standard CCR and BCC models, several units may receive an efficiency score of one. Consequently, these models do not necessarily provide a complete ranking of all efficient units. To address this limitation, various approaches have been developed to improve the discriminatory power of DEA and facilitate the ranking of DMUs.

One such approach is cross-efficiency, which was examined by Sexton et al. (1986). In this approach, each DMU is evaluated not only using its own optimal weights but also using the optimal weights obtained for other DMUs. This procedure can improve the differentiation among units; however, the resulting rankings may depend on how alternative optimal weights are determined and selected (Sexton et al., 1986).

Andersen and Petersen (1993) subsequently introduced the super-efficiency model, commonly referred to as the Andersen–Petersen (AP) model. In this approach, the DMU under evaluation is excluded from the reference set, and its efficiency is assessed relative to a frontier

constructed from the remaining units. This modification makes it possible to differentiate among units identified as efficient by conventional DEA models and provides a basis for ranking them. The AP model is therefore one of the established approaches for ranking efficient DMUs in DEA (Andersen & Petersen, 1993).

Another approach developed to provide a more detailed assessment of inefficiency is the slack-based measure (SBM), introduced by Tone (2001). By explicitly accounting for input excesses and output shortfalls, the SBM approach evaluates inefficiency based on the slacks associated with a DMU's position relative to the efficiency frontier. Although both SBM and AP belong to the DEA framework, they serve different purposes. SBM focuses on measuring inefficiency through input and output slacks, whereas AP is particularly used to distinguish and rank efficient units (Tone, 2001).

Following the introduction of the fundamental DEA models and early ranking approaches, researchers sought to extend DEA, particularly super-efficiency models, to address more complex decision-making environments. Some studies focused on improving the discriminatory power of efficiency assessments and developing alternative ranking procedures, while others examined uncertainty in the data and limitations of conventional models.

In this context, Khodabakhshi et al. (2007) proposed a super-efficiency model based on output improvement. By focusing on increasing output levels, their approach contributed to the development of super-efficiency methods and the improvement of ranking capabilities. These studies sought to overcome limitations of conventional approaches and enhance the ability to discriminate among efficient DMUs. Nevertheless, extended models may differ from the standard AP model in terms of returns-to-scale assumptions, orientation, and the calculation of efficiency scores (Khodabakhshi et al., 2007).

In subsequent research, Khodabakhshi et al. (2009) developed several super-efficiency models for stochastic environments. By incorporating uncertainty into the data, these models extended the DEA framework to situations in which input and output values are not known with certainty. This line of research reflects efforts to broaden the applicability of super-efficiency models to real-world problems and more complex decision-making environments (Khodabakhshi et al., 2009).

Furthermore, Khodabakhshi and Aryavash (2012) proposed a ranking approach known as the KA model. Based on optimistic and pessimistic perspectives, this method estimates the minimum and maximum efficiency scores of DMUs, thereby providing a means of examining the range of their potential performance. The ranking is determined by combining the minimum and maximum scores of each unit. This approach represents an effort to improve differentiation among DMUs and provide a more comprehensive ranking framework (Khodabakhshi & Aryavash, 2012).

Khodabakhshi et al. (2014) subsequently extended the KA model to rank DMUs in the presence of fuzzy data. In this approach, the minimum and maximum attainable efficiency scores of each unit are examined at different levels and represented as intervals to account for uncertainty in the scores. The units are then ranked according to the resulting fuzzy efficiency assessments. This extension broadens the applicability of DEA ranking methods to problems in which the available data are imprecise or uncertain (Khodabakhshi et al., 2014).

The applications of DEA extend beyond the development of mathematical models and ranking procedures to the evaluation of performance across different types of entities. For example, Amini et al. (2024) applied DEA to evaluate and rank Iranian provinces according to development indicators. Such applications demonstrate the potential of DEA not only for assessing the efficiency of organizations and production units but also for regional evaluation and performance measurement based on multiple indicators.

Overall, the evolution of DEA from the fundamental CCR and BCC models to ranking, super-efficiency, and extended approaches demonstrates its development into a broad framework for performance evaluation and decision support. At the same time, differences among available models highlight the importance of selecting an approach that is consistent with the research objectives and the characteristics of the problem under investigation.

Given the objective of the present study, which is to evaluate and rank 30 road transportation companies, DEA is employed to assess their relative efficiency, while the Andersen–Petersen (AP) super-efficiency model is used to rank the efficient DMUs. The AP model is selected because it can distinguish among units that receive an efficiency score of one under the conventional DEA framework. Accordingly, the proposed approach enables the identification of efficient and inefficient companies and facilitates further differentiation among efficient companies. In the following section, the mathematical formulations of the fundamental CCR and BCC models are first presented to establish the methodological foundation of DEA. The mathematical formulation of the AP model and its application to ranking the companies included in this study are then described.

## **1.2. Mathematical Formulations of the CCR, BCC, and AP Models**

To establish the mathematical framework of the methodology employed in this study, the general structures of the fundamental Data Envelopment Analysis (DEA) models, including the CCR and BCC models, are first introduced. These models provide the mathematical foundation for evaluating the relative efficiency of decision-making units (DMUs). Subsequently, given the output-oriented approach adopted in this study, the mathematical formulation of the Andersen–Petersen (AP) super-efficiency model is presented. Under this approach, the potential for increasing outputs while keeping inputs constant is examined. Furthermore, by excluding the unit under evaluation from the

reference set, the AP model enables the calculation of super-efficiency scores and the differentiation of efficient units based on their relative performance.

The CCR model, originally proposed by Charnes, Cooper, and Rhodes (1978), assumes constant returns to scale (CRS) and evaluates the relative efficiency of decision-making units. The output-oriented formulation of the CCR model is presented as follows:

$$\begin{aligned} & \max \theta \\ & \text{s.t.} \\ & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{io} \quad i = 1, 2, \dots, m \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq \theta y_{ro} \quad r = 1, 2, \dots, s \\ & \lambda_j \geq 0 \quad j = 1, 2, \dots, n \end{aligned}$$

In the above model,  $(n)$  denotes the number of decision-making units (*DMUs*),  $(m)$  represents the number of inputs, and  $(s)$  represents the number of outputs. Furthermore,  $(x_{ij})$  denotes the amount of input  $(i)$  used by DMU  $(j)$ ,  $(y_{rj})$  represents the amount of output  $(r)$  produced by DMU  $(j)$ , and  $(\lambda_j)$  denotes the weight assigned to each reference DMU. The variable  $(\theta)$  represents the proportional output expansion factor of the DMU under evaluation. In the output-oriented CCR model, the optimal value of these variable equals one for efficient DMUs and is greater than one for inefficient DMUs.

The output-oriented BCC model extends the CCR model by incorporating a convexity constraint, which allows for variable returns to scale (VRS). Similar to the CCR model, its objective is to maximize the proportional expansion of outputs while keeping inputs constant. The main difference between the two models is that the BCC model accounts for variations in scale efficiency by imposing the convexity constraint  $(\sum_{j=1}^n \lambda_j = 1)$ . The mathematical formulation of the output-oriented BCC model is presented below.

$$\begin{aligned} & \max \theta \\ & \text{s.t.} \\ & \sum_{j=1}^n \lambda_j x_{ij} \leq x_{io} \quad i = 1, 2, \dots, m \\ & \sum_{j=1}^n \lambda_j y_{rj} \geq \theta y_{ro} \quad r = 1, 2, \dots, s \\ & \sum_{j=1}^n \lambda_j = 1 \\ & \lambda_j \geq 0 \quad j = 1, 2, \dots, n \end{aligned}$$

In the above model, the variables and parameters have the same definitions as those in the output-oriented CCR model. In the BCC model, the constraint  $(\sum_{j=1}^n \lambda_j = 1)$ , known as the convexity constraint, ensures that the DMU under evaluation is compared only with convex combinations of the existing DMUs. Consequently, pure technical efficiency can be distinguished from the effects of scale.

Although conventional Data Envelopment Analysis (DEA) models, such as the CCR and BCC models, are used to evaluate the relative efficiency of decision-making units (DMUs), they generally assign an efficiency score of one to all efficient units. Consequently, when multiple units lie on the efficiency frontier, these models do not provide a direct means of ranking them based on their conventional efficiency scores. Therefore, supplementary ranking methods, such as super-efficiency models, are required to distinguish among efficient units and compare their relative performance.

Several methods have been developed to address this limitation, including the Andersen–Petersen (AP) super-efficiency model, cross-efficiency analysis, and other DEA-based ranking approaches. The Andersen–Petersen super-efficiency model is one of the well-established methods in this field. By excluding the DMU under evaluation from the reference set, it enables the calculation of super-efficiency scores and the ranking of efficient units.

In this study, the output-oriented Andersen–Petersen (AP) super-efficiency model is employed to rank the 30 road transportation companies. Under this approach, the potential for increasing outputs while keeping inputs constant is examined. Furthermore, by excluding the DMU under evaluation from the reference set, the model enables efficient units to be distinguished and ranked according to their super-efficiency scores. The mathematical formulation of the output-oriented AP super-efficiency model is presented below.

$$\begin{aligned}
 & \max \theta \\
 & \text{s.t.} \\
 & \sum_{\substack{j=1 \\ j \neq o}}^n \lambda_j x_{ij} \leq x_{io} \quad i = 1, 2, \dots, m \\
 & \sum_{\substack{j=1 \\ j \neq o}}^n \lambda_j y_{rj} \geq \theta y_{ro} \quad r = 1, 2, \dots, s \\
 & \sum_{\substack{j=1 \\ j \neq o}}^n \lambda_j = 1 \\
 & \lambda_j \geq 0 \quad j = 1, 2, \dots, n, \quad j \neq o
 \end{aligned}$$

Here,  $(o)$  denotes the DMU under evaluation, which is excluded from the reference set in the super-efficiency model to enable the ranking of efficient DMUs. Accordingly,  $(j \neq o)$  is imposed in the model.

Following the presentation of the mathematical formulation of the output-oriented Andersen–Petersen (AP) super-efficiency model, the next step is to determine the input and output indicators used to evaluate and rank road transportation companies. Within the Data Envelopment Analysis (DEA) framework, the appropriate selection of inputs and outputs plays an important role in determining the efficiency frontier and the resulting evaluation outcomes. Therefore, the selected indicators should be directly aligned with the research objectives and adequately reflect the operational, financial, and service-related performance of transportation companies. The following section introduces and describes the indicators used in this study.

### 1.3. Indicators Used in the Evaluation

To implement the output-oriented Andersen–Petersen (AP) model, a key step is to select indicators that accurately and comparably reflect the actual multidimensional performance of road construction and transportation companies. Since this study adopts an output-oriented approach, all selected indicators are treated as outputs and are intended to measure the results, capabilities, and achievements of the companies.

Considering the nature of the activities performed by the companies under study and the need for a comprehensive evaluation, the output indicators are classified into four main categories:

1. **Financial Performance:** This category reflects the financial performance of the companies and plays a significant role in assessing the returns generated by their activities.
2. **Key Projects and Achievements:** This category refers to activities or projects that contribute significantly to improving company performance or competitive advantage through innovation, substantial improvements, or other notable achievements.
3. **Contracts:** The ability to secure, manage, and execute various contracts in the road construction and transportation sectors represents another key dimension of performance assessed through this category.
4. **Human Resources (Managers' and Employees' Scores):** The performance and contributions of managers and employees are important factors influencing organizational outcomes and are incorporated through indicators related to human resource evaluation.

These indicators have been selected to ensure compatibility with the operational structure of the companies under study, the requirements of the DEA framework, and the principles of data confidentiality. They form the basis for analyzing the performance of the 30-road construction and transportation companies selected for this study.

In this study, the companies are classified into four distinct groups, referred to as “tiers,” based on the indicators provided by the companies themselves. This classification is independent of the results obtained from the output-oriented Andersen–Petersen model and reflects the companies’ overall activity levels and relative positions based on the available data and indicators. Tier A represents the highest level of performance and quality of activities, with companies in this tier demonstrating stronger overall indicators and capabilities. Companies assigned to Tiers B, C, and D represent progressively lower performance levels. However, companies in these tiers may have the opportunity to advance to a higher tier by achieving better scores on the evaluated indicators.

To maintain the confidentiality and security of the information provided by the companies, their full names are not disclosed; instead, an anonymization-based coding system is used. Each tier is represented by an English letter from A to D, and the companies within each tier are numbered sequentially (e.g., A1, A2, and so on). This coding system enables analytical presentation and comparison of the results without disclosing confidential company information, while preserving the ability to identify and reference each company consistently throughout the study.

## **2. Results of the AP Super-Efficiency Model**

### **2.1. Empirical Efficiency Scores and Cross-Tier Distribution**

This section presents the results obtained from applying the output-oriented Andersen–Petersen (AP) super-efficiency model to the performance data of 30 companies operating in the road construction and transportation sector. In this model, each decision-making unit (DMU) is evaluated after being excluded from the reference set, allowing the companies to be differentiated and ranked according to their relative performance. The detailed efficiency scores and individual rankings are reported in Table 1, while Table 2 provides a comparative cross-tier analysis accompanied by a Spearman rank correlation to assess the structural consistency of the proposed model.

In the output-oriented Andersen–Petersen (AP) super-efficiency model, the resulting scores must be interpreted in accordance with the mathematical formulation of the model and its scoring convention. In the model adopted in this study, scores below one indicates efficient and super-efficient companies that achieve better positions in the final ranking. A score equal to one indicates that a company lies on the baseline efficiency frontier, whereas scores greater than one indicate relative inefficiency compared with the frontier formed by the other companies.

According to the results presented in Table 1, company B7, belonging to Tier 2, achieved the best relative performance among the 30 companies evaluated, with a super-efficiency score of 0.266 and a first-place ranking. Company A5, from Tier 1, ranked second with a score of 0.748. Since both companies obtained scores below one, they are classified as super-efficient benchmarks. Furthermore,

companies A3, A4, and A7, with scores of 0.998, 0.999, and 1.000, respectively, ranked third, fourth, and fifth, representing the top performers operating at or near the baseline efficiency frontier.

In contrast, company D8 obtained a score of 3.945 and ranked thirtieth, representing the least efficient unit. Companies D4 and D2 followed, with scores of 3.858 and 3.830, ranking twenty-ninth and twenty-eighth, respectively. These results indicate relatively weaker performance by these companies based on the indicators included in the model and suggest the need for a more detailed examination of their operational and managerial processes. However, identifying the causes of inefficiency and determining appropriate corrective measures require a separate assessment of resource utilization, outputs produced, and the companies' operating conditions.

A comparison of the DEA results with the initial company classification reveals that the quantitative ranking does not necessarily correspond to the contractors' original tier assignments. For example, company B7, initially classified in Tier 2, achieved the highest rank in the AP model-based evaluation. This finding suggests that, based on the selected performance indicators, some companies assigned to lower tiers may achieve better relative performance than certain companies in higher tiers. Therefore, the application of quantitative, data-driven methods can provide valuable supplementary information for evaluating contractors and reviewing the existing classification system.

**Table 1.** Evaluation and Ranking of Companies Using the Output-Oriented Andersen–Petersen (AP) Super-Efficiency Model

| No.    | Company | Super-Efficiency Score | Rank | No.    | Company | Super-Efficiency Score | Rank |
|--------|---------|------------------------|------|--------|---------|------------------------|------|
| Tier 1 |         |                        |      | Tier 3 |         |                        |      |
| 1      | A1      | 1.008                  | 6    | 16     | C1      | 1.723                  | 16   |
| 2      | A2      | 1.047                  | 9    | 17     | C2      | 2.501                  | 22   |
| 3      | A3      | 0.998                  | 3    | 18     | C3      | 2.101                  | 19   |
| 4      | A4      | 0.999                  | 4    | 19     | C4      | 1.697                  | 15   |
| 5      | A5      | 0.748                  | 2    | 20     | C5      | 2.576                  | 23   |
| 6      | A6      | 1.031                  | 8    | 21     | C6      | 2.333                  | 20   |
| 7      | A7      | 1.000                  | 5    | 22     | C7      | 2.022                  | 18   |
| 8      | A8      | 1.030                  | 7    | Tier 4 |         |                        |      |
| Tier 2 |         |                        |      | 23     | D1      | 3.373                  | 26   |
| 9      | B1      | 1.688                  | 14   | 24     | D2      | 3.830                  | 28   |
| 10     | B2      | 1.389                  | 10   | 25     | D3      | 3.543                  | 27   |
| 11     | B3      | 1.610                  | 12   | 26     | D4      | 3.858                  | 29   |
| 12     | B4      | 1.728                  | 17   | 27     | D5      | 3.299                  | 25   |
| 13     | B5      | 1.649                  | 13   | 28     | D6      | 2.471                  | 21   |
| 14     | B6      | 1.479                  | 11   | 29     | D7      | 3.278                  | 24   |
| 15     | B7      | 0.266                  | 1    | 30     | D8      | 3.945                  | 30   |

**Table Note:** Efficiency scores are reported rounded to Three decimal places. The rankings are strictly determined based on full-precision solver results, which accounts for distinct ranks among seemingly close values (e.g., DMU3, DMU4, and DMU7)

To gain deeper cross-tier insights and evaluate how closely the empirical DEA rankings align with the traditional administrative classification, Table 2 summarizes the distribution of super-efficiency scores and ranks across the four contractor tiers.

**Table 2.** Descriptive comparison between administrative contractor tiers and DEA super-efficiency ranks

| Contractor Tier | Number of DMUs | Best DEA Rank | Worst DEA Rank | Mean Rank | Mean Score |
|-----------------|----------------|---------------|----------------|-----------|------------|
| Tier 1 (A1–A8)  | 8              | 2             | 9              | 5.50      | 0.983      |
| Tier 2 (B1–B8)  | 8              | 1             | 17             | 11.14     | 1.359      |
| Tier 3 (C1–C7)  | 7              | 15            | 23             | 19        | 2.137      |
| Tier 4 (D1–D7)  | 7              | 24            | 30             | 26.25     | 3.449      |

As reported in Table 2, an evident monotonic gradient exists between the administrative tiers and their overall operational efficiency. Tier 1 companies exhibit the most favorable collective performance, with a mean rank of 5.50 and an average efficiency score of 0.983, spanning ranks from 2 to 9. Tier 2 follows with a mean rank of 11.14 and an average score of 1.359; notably, this tier encompasses the top-ranked unit overall (company B7, rank 1), reflecting internal heterogeneity among mid-tier contractors. Tier 3 and Tier 4 show progressively declining efficiency levels, registering mean ranks of 19.00 and 26.25, and mean super-efficiency scores of 2.137 and 3.449, respectively. The least efficient tier, Tier 4, encompasses ranks from 21 to 30. While these descriptive indicators visually demonstrate a declining performance trend from Tier 1 to Tier 4, this structural alignment requires formal statistical validation. To quantify the strength and significance of the relationship between the administrative tier system and the DEA super-efficiency rankings, Spearman's rank correlation coefficient is computed directly in the following subsection.

## 2.2. Statistical Validation via Spearman's Rank Correlation

From a methodological standpoint, Spearman's rank correlation coefficient is employed because administrative contractor tiers represent ordinal categorical data that violate the bivariate normality assumptions required for parametric tests such as Pearson's correlation. To resolve tied ranks within each administrative category, the standard "average rank" approach is applied:

- Tier 1 ( $n_1 = 8$ , occupying ranks 1 to 8):

$$\bar{R}_{Tier1} = \frac{\sum_{r=1}^8 r}{8} = 4.5$$

- Tier 2 ( $n_2 = 7$ , occupying ranks 9 to 15):

$$\bar{R}_{Tier2} = \frac{\sum_{r=9}^{15} r}{8} = 12.0$$

- Tier 3 ( $n_3 = 7$ , occupying ranks 16 to 22):

$$\bar{R}_{Tier3} = \frac{\sum_{r=16}^{22} r}{7} = 19.0$$

- Tier 4 ( $n_4 = 8$ , occupying ranks 23 to 30):

$$\bar{R}_{Tier4} = \frac{\sum_{r=23}^{30} r}{8} = 26.5$$

To statistically assess the alignment between administrative contractor tiers and empirical performance ranks, we employ Spearman's rank correlation coefficient. Let  $R_{emp,i}$  denote the empirical rank derived from the AP super-efficiency DEA model for contractor  $i$ , and  $R_{admin,i}$  represent the assigned administrative average rank. The rank difference,  $d_i$ , is defined as:

$$d_i = R_{emp,i} - R_{admin,i}$$

where  $i = 1, 2, \dots, n$  (with  $n = 30$  representing the total sample size). Consequently, for any contractor ( $i$ ) belonging to a specific tier  $k$ , the administrative rank is assigned as  $R_{admin,i} = \bar{R}_{Tier k}$ .

Here, a negative value of  $d_i$  indicates that the contractor exhibits higher operational efficiency (a better rank) than its administrative tier implies, whereas a positive value signifies that its performance ranks lower than its official classification. Given the sum of squared rank differences calculated as  $\sum_{i=1}^n d_i^2 = 318.0$ , Spearman's rank correlation coefficient ( $\rho$ ) is mathematically formulated as:

$$\rho = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)}$$

Substituting these empirical values into the formula yields:

$$\rho = 1 - \frac{6 * 318}{30(900 - 1)} = 1 - \frac{1908}{26970} \approx 0.929$$

Adjusting for tied administrative ranks yields a standardized correlation coefficient of  $\rho = 0.927$ . To evaluate whether this observed alignment is statistically significant, a student's t-test is conducted with  $n - 2 = 28$  degrees of freedom ( $df$ ):

$$t = \rho \sqrt{\frac{n-2}{1-\rho^2}} = 0.927 \sqrt{\frac{28}{1-0.927^2}} = 13.12$$

With  $t(28) \approx 13.12$  and  $p < 0.001$ , the positive correlation between the administrative contractor tiers and the quantitative DEA rankings is statistically significant at the 1% significance level. This statistical outcome substantiates two essential conclusions:

1. Macro-Level Structural Alignment: The high correlation coefficient ( $\rho = 0.927$ ) confirms that the proposed quantitative DEA model strongly reflects the overarching hierarchical logic of the traditional administrative qualification system.

2. Micro-Level Discriminatory Power: While the overall system aligns well, specific performance anomalies-most notably company B7, which achieved the top overall empirical rank despite being classified in Tier 2-demonstrate that administrative tiers alone cannot capture operational efficiency. Consequently, the DEA super-efficiency model serves as a vital supplementary regulatory tool capable of identifying high-performing contractors across all tiers.

### 3. Discussion and Policy Implications

The results of the output-oriented Andersen–Petersen (AP) super-efficiency model reveal considerable differences in the relative performance of road construction and transportation companies based on the selected output indicators. Under the scoring convention used in this study, companies with super-efficiency scores below one occupies better positions in the resulting ranking, whereas scores above one indicates relatively weaker performance. A score of exactly one represents the reference efficiency level under the model’s scoring convention.

The results also indicate that a company’s administrative tier does not necessarily correspond to its relative position in the DEA-based ranking. For example, company B7, classified in Tier 2, achieved the highest rank (first place) with a score of 0.266. Company A5, classified in Tier 1, ranked second with a score of 0.748, whereas company D8, classified in Tier 4, ranked thirtieth with a score of 3.945. These differences illustrate the potential value of complementing conventional administrative classification with quantitative performance assessment. However, the DEA results should not be interpreted as definitive evidence of managerial quality or actual resource productivity, particularly because the implemented model focuses on output indicators and does not incorporate the companies’ actual input levels.

For companies occupying weaker positions in the DEA-based ranking, further investigation may help identify potential areas for improvement. Relevant areas for examination include operational processes, technical training, quality management, risk management, and the adoption of appropriate technologies. Nevertheless, specific recommendations should be based on a detailed assessment of the indicators and operating conditions of each company rather than inferred from the overall DEA score alone.

From a policy perspective, the proposed quantitative approach can provide supplementary information for regulatory authorities and organizations responsible for contractor evaluation. Periodic performance assessments based on reliable and consistently collected data may help identify differences between contractors and inform decisions concerning contractor selection and classification. Such decisions should nevertheless consider additional criteria, including construction quality, occupational and road safety, cost control, compliance with project schedules, and contractual performance.

## 4. Conclusion

This study evaluated 30 road construction and transportation companies using an output-oriented Andersen–Petersen super-efficiency DEA model. The results revealed substantial variation in the companies' relative positions based on the selected output indicators. In particular, B7 ranked first with a score of 0.266, followed by A5 with a score of 0.748, whereas D8 ranked thirtieth with a score of 3.945. These findings demonstrate that the DEA-based ranking can distinguish between companies within and across administrative tiers, providing information that may complement the existing classification system.

The association between administrative tiers and DEA-based rankings can be assessed using Spearman's rank correlation coefficient. The coefficient and its statistical significance should be reported only after they have been verified using the paired rankings of all 30 companies and an appropriate procedure that accounts for tied ranks. Any observed association should be interpreted as evidence of rank concordance rather than proof that the two classification systems are equivalent or that the DEA model independently validates the administrative system.

Overall, the proposed approach offers a supplementary framework for comparing contractors based on selected output indicators. Its results may support more evidence-informed performance evaluation when considered alongside other technical, operational, safety, and managerial criteria.

### 4.1. Limitations of the Study

Despite the usefulness of the Andersen–Petersen super-efficiency model for differentiating the relative positions of decision-making units, several limitations should be acknowledged.

**Methodological scope.** The implemented model is output-oriented and focuses on the selected outputs without incorporating the companies' actual input levels. Consequently, it does not provide a comprehensive assessment of input utilization, input-oriented technical efficiency, or allocative efficiency. Future applications incorporating relevant input and output indicators could provide a more comprehensive evaluation.

**Data quality.** The reliability of the results depends on the accuracy, consistency, and comparability of the underlying data. If the data are obtained from administrative records or company-reported sources, potential measurement errors, reporting inconsistencies, and differences in data collection practices may affect the estimates.

**Sample and generalizability.** The analysis includes 30 decision-making units (DMUs). Although this sample enables comparison among the companies included in the study, the findings should not automatically be generalized to all road construction and transportation contractors, other geographical regions, or different time periods. The robustness of the rankings should be examined using additional observations and sensitivity analyses where data are available.

### 4.2. Directions for Future Research

Future research could extend the present analysis in several directions.

**Two-stage DEA and environmental factors.** A two-stage analytical framework could be used to investigate the relationship between estimated efficiency and contextual factors, such as company age, organizational structure, regional market conditions, and competitive environment. Depending on the research design and data structure, suitable regression or bootstrap-based procedures could be considered, with appropriate attention to the statistical properties of DEA efficiency estimates.

**Temporal dynamics.** Applying DEA to longitudinal data and using the Malmquist Productivity Index could help examine changes in productivity and efficiency over time. Such an analysis would make it possible to distinguish changes in relative efficiency from shifts in the production frontier.

**Uncertainty and data imprecision.** Stochastic or fuzzy DEA approaches could be explored when the data contain substantial measurement uncertainty, imprecision, or random variation. The suitability of each approach would depend on the nature of the uncertainty and the availability of supporting data.

**Multidimensional performance assessment.** Future studies could incorporate both input and output indicators and consider alternative DEA formulations, including the slacks-based measure (SBM). Such models could provide a more comprehensive assessment of input excesses and output shortfalls, subject to the suitability of the selected variables and model assumptions.

### **Conflict of Interest**

The authors declare that there are no conflicts of interest associated with the conduct of this research or the publication of its results.

### **Authors' Contributions**

All authors contributed to the preparation of the manuscript. The nature and extent of each author's contribution will be reported in accordance with their actual contributions, if required by the journal.

### **Ethical Considerations**

The principles and standards of research ethics were observed throughout the conduct of this study.

### **Data Transparency**

The data used in this study may be made available upon request to the corresponding author, subject to intellectual property rights, access restrictions, and confidentiality requirements.

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