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Evaluating Financial Performance of Exchange-Listed Companies with Integrated DEA and Malmquist Index

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ABSTRACT

Objective: A stock exchange is a formal market where companies' shares are traded. Therefore, examining the efficiency of companies listed on the stock exchange is of significant importance. One of the main shortcomings of existing financial performance evaluation methods is their emphasis on a single key indicator and their reliance on subjective judgments. This study aims to evaluate the financial performance of selected companies listed on the stock exchange using a hybrid approach combining Data Envelopment Analysis (DEA) and the Malmquist Productivity Index.

Methodology: In this research, to overcome the limitations of traditional analyses based on financial ratios, such as their one-dimensional nature, potential to be misleading, and difficulty of interpretation, the Data Envelopment Analysis technique is employed to assess corporate performance. This method aggregates multiple financial ratios and assigns each company a single score, called efficiency. Moreover, the Malmquist Productivity Index, an important concept in DEA, is used to evaluate changes in the efficiency of a decision-making unit over two time periods.

Results: Based on this study's results, in almost all years, the symbols Sebahan in the mining industry, Khodro in the automotive industry, and Foolad in the basic metals industry ranked first. Therefore, it is recommended that investors considering these industries base their investment decisions on these results.

Conclusion: This article presents a combined application of Data Envelopment Analysis and the Malmquist Productivity Index and evaluates the financial performance of selected companies listed on the stock exchange.

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Introduction

Performance evaluation is central to corporate governance, investor decisions, regulatory oversight, and market efficiency. Financial performance metrics, including profitability, liquidity, solvency, efficiency, and cash flows, summarize a firm's ability to meet obligations, generate returns, and sustain operations; these summaries underpin investors' portfolio selection, lenders' credit decisions, managers' strategic choices, and policy makers' assessments of sector health (Fahami et al., 2019; Lam et al., 2023). In capital markets, reliable performance evaluation supports the allocation of capital to more productive firms and reduces information asymmetry between managers and investors. Multi-criteria decision-making (MCDM) and quantitative performance models are widely used in the literature to rank firms, compare sectors, and inform investment decisions, with studies employing TOPSIS, VIKOR, fuzzy MCDM, DEA, and other hybrid approaches to provide robust relative evaluations across multiple financial dimensions (Dagistanli, 2023; Fahami et al., 2019; W. H. Lam et al., 2023; W. S. Lam et al., 2021).

During economic shocks, such as the COVID-19 pandemic, company financials can diverge sharply across industries and firms. Accurate and comprehensive evaluation methods help detect vulnerabilities, such as weak liquidity or solvency, and identify resilient firms for portfolio selection or regulatory attention (Baydaş, 2022; Makki & Alqahtani, 2023). Iran's financial system and regulatory environment face structural challenges that can impair efficient capital allocation. Recent research emphasizes the need for reforms in the financial regulatory system to improve the effectiveness and resilience of markets and firms in Iran (Abutorabi & Hajamini, 2024). Given these systemic issues, there is a heightened need for rigorous, objective methods to evaluate firm financial performance in Iranian capital markets, enabling investors, managers, and regulators to make informed decisions. Objective, comparative performance assessments can help overcome inconsistent reporting, reduce information asymmetry, and support prioritization of reforms and capital allocation in the Iranian context (Abutorabi & Hajamini, 2024; Hirad, 2014). Furthermore, sectoral and firm-level performance following shocks, whether pandemic- or sanctions-driven, must be tracked using methods that capture both efficiency and dynamics over time, rather than static ratios alone, to reveal productivity trends and guide policy and investment under uncertainty (Baydaş, 2022; Makki & Alqahtani, 2023).

Data Envelopment Analysis (DEA) is a nonparametric frontier method that evaluates the relative technical efficiency of decision-making units (firms) using multiple inputs and outputs without requiring an explicit functional form. DEA has been widely applied to corporate and sectoral performance evaluation to identify efficient peers and sources of inefficiency (Hirad, 2014, pp. 44–59; Liu et al., 2019). The Malmquist Productivity Index (MPI) extends DEA by measuring productivity change over time. It decomposes total factor productivity change into efficiency change, representing "catching up" to the frontier, and technical change, representing shifts in the frontier. This decomposition is crucial when research objectives include tracking performance dynamics, productivity growth or decline, and the factors driving change across periods, such as pre- and post-event periods, policy shifts, or economic shocks (Abdel-Basset et al., 2020; Liu et al., 2019).

Combining DEA and MPI as a hybrid dynamic efficiency-productivity approach offers several advantages for financial performance evaluation. It accommodates multiple financial inputs and outputs, such as capital, costs, revenues, and returns, without requiring a priori price or weight assumptions (Hirad, 2014; Liu et al., 2019). It provides relative efficiency scores for cross-sectional ranking and benchmarking, which are helpful for investor portfolio selection and for comparing managerial performance (Fahami et al., 2019; Liu et al., 2019). MPI captures temporal changes and identifies whether observed productivity changes arise from improved efficiency, such as managerial or operational improvements, or from technical and market shifts, information that static ratio-based or single-period MCDM methods cannot reveal (Abdel-Basset et al., 2020; Liu et al., 2019). The literature shows a proliferation of MCDM and hybrid methods for firm financial evaluation, including TOPSIS, VIKOR, and fuzzy variants. However, DEA, combined with MPI, specifically addresses dynamic efficiency and productivity, which are essential when evaluating companies listed on a stock exchange over multiple years and through economic disturbances (Abdel-Basset et al., 2020; W. H. Lam et al., 2023; W. S. Lam et al., 2021).

Contributions

This study contributes in three ways:

(1) Methodological integration: we operationalize a transparent hybrid pipeline (FAHP → composite financial input/output construction → SBM-DEA efficiency → SBM-based Malmquist productivity) so that both cross-sectional efficiency and intertemporal productivity can be jointly used for ranking.

(2) Non-radial dynamic measurement: instead of radial DEA–MPI, we use SBM distances (and Super-SBM when required) to incorporate slacks and avoid biased productivity estimates in the presence of non-proportional input/output adjustments.

(3) Empirical insight for TSE non-financial firms (2013–2016): we provide industry-wise efficiency/productivity patterns and highlight consistent top performers that can be used as benchmarks by managers and investors.

Literature Background

Dutta et al. (2020) analyzed the performance of non-banking finance companies (NBFCs) in India using a two-stage data envelopment analysis (DEA). In the first stage, super-efficiency scores were calculated using panel data from 2014–2018, and in the second stage, a Tobit regression was applied to identify exogenous factors affecting efficiency. The study also employed Malmquist indices to assess productivity changes over 5 years and to examine efficiency differences across NBFCs of varying sizes. The objectives were to evaluate overall efficiency, identify performance determinants, and provide managerial insights to improve productivity and operational decision-making. Peykani et al. (2025) proposed a robust Malmquist productivity index (RMPI) to measure productivity changes of decision-making units (DMUs) over time under uncertainty. The study extended the Malmquist productivity index (MPI) and data envelopment analysis (DEA) models using a robust optimization approach to address data uncertainty. The method was applied to 15 actively traded petroleum product stocks on the Tehran Stock Exchange over 2 years. The objectives were to evaluate DMU performance in terms of progress, regression, and stagnation, and to identify productivity trends under uncertain conditions.

Sunardi et al. (2025) analyzed the efficiency and productivity of Bank NTB Syariah before and after its conversion using data envelopment analysis (DEA) and the Malmquist productivity index (MPI). DEA was applied to measure efficiency using the MAXDEA software, while MPI was used to assess productivity changes with the DEAP software. The study found a decline in productivity before conversion and an increase after, with technological change (TECHCH) identified as the main driver of productivity shifts. The objectives were to evaluate efficiency and productivity trends and provide managerial guidance for technological adoption to enhance bank performance. Amirteimoori et al. (2024) developed a firm-specific Malmquist productivity index model based on stochastic data envelopment analysis (DEA) to examine efficiency and productivity changes in commercial banks. A two-stage double bootstrap DEA was used to estimate bank-specific technical efficiency and assess the impact of contextual variables, while a second two-stage procedure measured productivity change and its determinants.

The model was applied to 120 bank-year observations of 15 Iranian banks from 2014 to 2021. The objectives were to evaluate efficiency and productivity under stochastic variability and to identify factors, such as the nonperforming loan ratio and branch numbers, that influence bank performance for managerial optimization. Kamel et al. (2021) assessed the financial efficiency of twelve commercial banks listed on the Egyptian Stock Exchange using data envelopment analysis (DEA) and the Malmquist productivity index (MPI) for 2017–2019. The study applied BCC-I, cross-efficiency, and super-efficiency models, with R Studio used for computations. Results showed that only four banks were efficient under BCC-I, with CIB being the most efficient overall. At the same time, MPI indicated a general decline in financial efficiency due to reduced technological innovation. Tobit regression identified total assets and total equity as significant determinants of efficiency.

The objectives were to evaluate financial efficiency trends and provide insights for stakeholders to improve banking performance and inform financial policies. Ouertani (2025) measured productivity and efficiency changes of 26 insurance companies in Saudi Arabia using data envelopment analysis (DEA) combined with the Malmquist productivity index for 2019–2022. The study decomposed total productivity changes into technological progress and technical efficiency, finding that technological advancements drove productivity growth. In contrast, technical efficiency declined for some insurers due to poor resource management. The objectives were to evaluate total factor productivity, identify drivers of performance changes, and provide managerial guidance for adopting innovative practices to enhance efficiency and overall productivity.

Sovero Rivera (2022) estimated the financial efficiency of 76 companies listed on the Lima Stock Exchange across Agrarian, Industrial, Public Services, and Mining sectors from 2015 to 2020 using data envelopment analysis (DEA) and the Malmquist productivity index (MPI). The study found Mining to be the most efficient sector and Agrarian the least, with efficiency changes driving productivity growth while technological change contributed minimally. The objectives were to assess sectoral performance, analyze productivity and efficiency trends, and provide insights to support investment decisions despite macroeconomic fluctuations. Bosomtwe et al. (2025) assessed the efficiency and productivity changes of 19 banks in Ghana from 2015 to 2023 using data envelopment analysis (DEA) and the Malmquist productivity index (MPI).

The study applied input-oriented intermediation models, including CCR and BCC DEA models, to evaluate overall, purely technical, and scale efficiency. At the same time, MPI decomposed total factor productivity into technical and efficiency changes. Results indicated general efficiency improvements, but technical change was the main driver of productivity decline. The objectives were to measure bank efficiency and productivity trends, identify key sources of inefficiency, and provide guidance for technological investment and managerial improvement in the banking sector. Colak (2023) measured the efficiency of 20 real estate investment trusts (REITs) traded on BIST using data envelopment analysis (DEA) and the Malmquist total factor productivity index for 2019–2021. The study analyzed changes in efficiency and productivity using financial ratios, including the current ratio, leverage, debt-to-asset ratio, equity-to-asset ratio, return on assets, net profit margin, and gross profit margin. Results identified eight relatively efficient REITs and highlighted the need for less efficient firms to adjust input variables to improve performance. The objectives were to evaluate efficiency and productivity trends and provide actionable insights for managerial decision-making in the real estate investment sector. Foroghi Mazandaran et al. (2025) identified and ranked the financial inefficiency factors of companies listed on the Tehran Stock Exchange using a combined approach of data envelopment analysis (DEA) and artificial neural networks (ANN).

In the first stage, DEA was applied to evaluate company efficiency. In the second stage, ANN analyzed the efficiency scores to determine and prioritize the key factors contributing to financial inefficiency. The objectives were to measure efficiency, identify drivers of inefficiency, and provide a ranked framework to guide managerial and policy interventions to improve performance. The literature on efficiency and productivity measurement demonstrates extensive use of data envelopment analysis (DEA) and the Malmquist productivity index (MPI) across different industries and countries. Researchers have applied these methods to banks, insurance companies, stock markets, and real estate investment trusts to evaluate operational performance, identify efficiency determinants, and provide managerial guidance. The integration of DEA with MCDM methods to overcome ranking limitations is a well-established stream in performance evaluation literature.

A pertinent example within the scope of this journal is the work of Soltani and Soltani (2025), who developed a two-stage DEA–PROMETHEE II framework to achieve a complete ranking of global retail firms. Their study effectively demonstrates that supplementing DEA efficiency scores with key financial ratios (e.g., ROA, ROE) using an MCDM technique can resolve the issue of multiple efficient units and yield a preferred order for decision-makers. This aligns with the core objective of the present study, which also seeks to provide a comprehensive ranking. However, while their approach offers a robust cross-sectional ranking for a specific period, our methodology adopts a longitudinal perspective by integrating DEA with the Malmquist Productivity Index to capture and rank firms based on their dynamic productivity changes over time.

Despite extensive applications of DEA–MPI in banking and insurance, fewer studies focus on **non-financial listed firms** using a **non-radial (SBM) dynamic productivity framework** and provide a precise mechanism to incorporate expert-based importance of financial indicators. Many studies either (i) rely on radial models that ignore slacks, (ii) evaluate only a single sector, or (iii) do not clarify how multiple financial ratios are operationalized as DEA inputs/outputs. This study addresses these gaps by (a) constructing composite financial inputs/outputs using FAHP-derived weights, (b) estimating efficiency via SBM-DEA, and (c) measuring productivity change via SBM-based Malmquist decomposition for TSE firms during 2013–2016. A summary of these studies, including their methods, data periods, key variables, findings, and research objectives, is presented in Table 1.

Table 1. Summary of Previous Studies on Efficiency and Productivity Measurement Using DEA and Malmquist Index

Authors & Year	Application Area	Methods / Models	Data Period	Variables / Indicators	Key Findings	Research Objectives
Dutta et al. (2020)	Non-banking finance companies in India	Two-stage DEA, Tobit Regression, Malmquist Index	2014–2018	Super-efficiency scores, exogenous factors	Efficiency differences across NBFCs by size; key factors affecting performance identified	Evaluate overall efficiency, identify performance determinants, and provide managerial insights
Peykani et al. (2025)	Petroleum stocks on the Tehran Stock Exchange	DEA, Malmquist Index, Robust Optimization	2 years	Productivity changes under uncertainty	Many stocks showed declining productivity	Evaluate DMU performance in terms of progress, regression, stagnation; identify productivity trends under uncertainty
Sunardi et al. (2025)	Bank NTB Syariah	DEA (MAXDEA), Malmquist Index (DEAP)	Pre- and post-conversion	Productivity changes, TECHCH	Productivity declined before and increased after conversion; technological change (TECHCH) is the primary driver	Assess efficiency and productivity trends; provide managerial guidance for technology adoption
Amirteimoori et al. (2024)	Commercial banks in Iran	Two-stage Double Bootstrap DEA, Malmquist Index	2014–2021	Non-performing loan ratio, number of branches	Contextual variables are inversely related to efficiency and productivity	Evaluate efficiency and productivity under stochastic variability; identify

						influential factors
Kamel et al. (2021)	Commercial banks in Egypt	DEA (BCC-I, Cross-efficiency, Super-efficiency), Malmquist Index, Tobit Regression	2017–2019	Total assets, total equity	Overall decline in productivity due to low technological innovation; CIB is the most efficient	Assess financial efficiency trends; guide policy and performance improvement
Ouertani (2025)	Insurance companies in Saudi Arabia	DEA, Malmquist Index	2019–2022	Technological progress, technical efficiency	Productivity growth driven by technology; technical efficiency declined in some firms	Assess total factor productivity; identify performance drivers; provide managerial guidance for innovation adoption
Sovero Rivera (2022)	Companies listed on the Lima Stock Exchange	DEA, Malmquist Index	2015–2020	Agrarian, Industrial, Public Services, and Mining sectors	The mining sector is the most efficient; efficiency change drove productivity; technological change is minimal	Evaluate sectoral performance; analyze productivity and efficiency trends; support investment decisions
Bosomtwe et al. (2025)	Banks in Ghana	DEA (CCR, BCC), Malmquist Index	2015–2023	Overall, purely technical, scale efficiency	Efficiency improved overall; technical change was the primary source of productivity decline	Assess bank efficiency and productivity trends; identify inefficiency sources; guide technological investment
Colak (2023)	REITs traded on BIST	DEA, Malmquist Index	2019–2021	Financial ratios: current ratio, leverage, debt-to-asset, equity-to-asset, ROA, net and gross profit margin	Eight REITs were identified as efficient; less efficient firms need to adjust their inputs	Evaluate efficiency and productivity; provide managerial guidance for performance improvement

Materials and Methods

As stated earlier, the main objective of this study is to evaluate the financial performance of selected companies listed on the stock exchange using a hybrid approach of Data Envelopment Analysis (DEA) and the Malmquist Productivity Index. Accordingly, the central research question is as follows: To what extent are the efficiency and productivity of selected companies listed on the stock exchange, and how will these companies be ranked based on their levels of efficiency and productivity?

The present study is applied in purpose and descriptive in data collection method. In terms of nature, it is a quantitative study employing mathematical modeling. With respect to the thematic, temporal, and spatial scope, this research falls within the domain of performance management and, more specifically, within the subfield of financial performance evaluation (efficiency and productivity assessment). The study is longitudinal, covering the period from 2013 to 2016, and is conducted within the context of the Tehran Stock Exchange. The study's statistical population comprises all companies listed on the Tehran Stock Exchange during the period from 2013 to 2016. In selecting the statistical sample, two key considerations were taken into account: (1) the sample should be a suitable representative of the statistical population, and (2) the sample should be consistent with the main variables of the study. Accordingly, the research sample was selected based on the following criteria:

1. The company is not classified as an investment company, bank, insurance company, or financial intermediary.
2. The company was listed on the Tehran Stock Exchange prior to 2005.

To select the research sample, judgmental sampling combined with systematic elimination was employed. In this approach, the necessary conditions for sample selection are first defined, and companies that do not meet these criteria are excluded. The rationale for using this method and defining these conditions is to homogenize the statistical sample with the overall population and to enable generalizing the test results to the statistical population. The evaluation criteria used in this study were initially identified through a literature review of books and scientific articles (previous studies), summarized in Table 1 and the empirical background section. These criteria were then refined through field investigation and group interviews with stock market experts. Finally, the required data were collected from companies’ financial statements, the Tehran Stock Exchange's official website, and other relevant sources using a field data-collection approach.

Research Procedure

The study followed a systematic procedure to evaluate financial performance:

1. **Sample Selection:** Companies listed on the TSE from 2013 to 2016 were filtered based on predefined criteria to ensure homogeneity.
2. **Variable Identification:** Input and output variables were identified through a comprehensive literature review and finalized through consultations with stock market experts.
3. **Criteria Weighting:** The Fuzzy AHP (FAHP) method was employed to determine the relative importance (weights) of the primary and sub-criteria derived from the financial ratios.
4. **Data Collection and Compilation:** Financial data for the selected variables were collected from audited financial statements and the TSE database for the period 2013-2016.
5. **Efficiency Measurement (DEA):** The weighted input and output data for each company-year were analyzed using the non-oriented SBM model (Tone, 2001) to calculate annual technical efficiency scores.
6. **Productivity Change Measurement (MPI):** The Malmquist Productivity Index was computed using the SBM distances to decompose productivity changes into efficiency change (catch-up) and technological change (frontier-shift) components between consecutive years.
7. **Analysis and Ranking:** Companies and industries were ranked based on their efficiency scores and MPI values, and the results were analyzed to identify trends and top performers.

Fuzzy AHP for Criteria Weighting

To assign weights to the six main criteria and their sub-criteria, a two-level Fuzzy Analytic Hierarchy Process (FAHP) was utilized. This method incorporates expert judgment while handling the inherent ambiguity in pairwise comparisons (Buckley, 1985). Triangular fuzzy numbers (TFNs) were used for the pairwise comparison matrices. The steps were as follows:

1. A panel of 10 stock market experts was asked to perform pairwise comparisons of the criteria.
2. The linguistic judgments were converted into TFNs (e.g., "Equally Important" = (1,1,1), "Moderately More Important" = (2,3,4)).
3. The fuzzy pairwise comparison matrices were aggregated using the geometric mean method.

4. The fuzzy weights for each criterion were calculated using *Chang's extent analysis* method (Chang, 1996).
5. Finally, the fuzzy weights were defuzzified using the Center of Area method to obtain crisp weights. The resulting weights for the main criteria and sub-criteria are presented in the formulation of the input/output variables in Section 3.3 (e.g., coefficients such as 0.005 for Total Asset Turnover). The detailed fuzzy comparison matrices and intermediate calculations are omitted for brevity but are available upon request.

Research Variables

Based on the definition of input and output criteria, the final criteria were classified into two groups: input variables and output variables, as presented below:

A) Inputs:

In general, an input is a factor whose increase. In contrast, holding all other factors constant reduces efficiency, whereas decreasing all other factors results in an improvement in efficiency.

1) Activity Ratios:

A company's asset management efficiency is measured using activity ratios. Efficiency refers to the rapid turnover of assets; therefore, these ratios are called activity ratios. In calculating this type of ratio, greater emphasis is placed on certain asset items, such as inventories or accounts receivable. At the same time, in other cases, the company's overall activity is considered (Nouralidokht, 2014). The activity ratios in this study were calculated as follows:

Activity Ratios =

$$
\begin{aligned}
&[(\text{Total Asset Turnover} \times 0.005) + (\text{Fixed Asset Turnover} \times 0.006) \\
&\qquad + (\text{Accounts Payable Turnover} \times 0.005) + (\text{Accounts Payable Payment Period} \\
&\qquad \times 0.013)] \\
&-[(\text{Total Inventory Turnover} \times 0.008) + (\text{Total Inventory Turnover Period} \times 0.007) \\
&\qquad + (\text{Accounts Receivable Turnover} \times 0.004) + (\text{Average Collection Period} \\
&\qquad \times 0.013) + (\text{Operating Cycle Period} \times 0.018)]
\end{aligned}
$$

This formulation reflects the combined weighted effect of various activity-related financial ratios used as input variables in the efficiency analysis.

2) Capital Structure Ratios:

Creditors focus on the amount of capital provided by the company's shareholders because, if the shareholders' share is lower than creditors', the company's risk will be borne primarily by creditors (Colak, 2023; Nouralidokht, 2014). As liabilities increase, interest expenses also rise, and if interest costs and debt levels become excessive, the likelihood of corporate distress and bankruptcy increases. However, if a company can use debt to finance desirable investment opportunities and the returns on these investments exceed the interest cost on the debt, shareholders' wealth will increase accordingly. The capital structure ratios were calculated as follows:

Capital Structure Ratios =

$$[(\text{Interest Coverage Ratio} \times 0.044) + (\text{Ratio of Fixed Assets to Equity} \times 0.027)] \\ -[(\text{Debt Ratio} \times 0.032) + (\text{Long-Term Debt to Equity Ratio} \times 0.027) \\ + (\text{Current Debt to Equity Ratio} \times 0.027) + (\text{Total Debt to Equity Ratio} \\ \times 0.027) + (\text{Debt Coverage Ratio} \times 0.036)]$$

3) Production Cost Ratios:

The production cost ratios were calculated as follows (Fahami et al., 2019):

Production Cost Ratios =

$$[(\text{Cost of Manufactured Goods Sold to Sales Ratio} \times 0.013) + (\text{Direct Labor Cost to Sales Ratio} \\ \times 0.013) + (\text{Manufacturing Overhead Cost to Sales Ratio} \times 0.013) \\ + (\text{Total Administrative and General Expenses to Sales Ratio} \times 0.011)]$$

B) Outputs:

An output is a factor whose decrease, while all other factors are held constant, leads to a reduction in efficiency, and whose increase, with all other factors unchanged, leads to an improvement in efficiency.

1) Liquidity Ratios:

Liquidity ratios are related to current assets and current liabilities. They are obtained by comparing current assets ,which can be converted into cash within a normal operating cycle or within one year from the balance sheet date, whichever is longer ,with current liabilities (Kamel et al., 2021; Nouralidokht, 2014). Liquidity ratios were calculated as follows:

Liquidity Ratios =

$$[(\text{Current Ratio} \times 0.035) + (\text{Quick Ratio} \times 0.024) + (\text{Working Capital} \times 0.022)]$$

2) Profitability Ratios:

One of the most important indicators of a company's financial health and managerial efficiency is its ability to generate acceptable profits or satisfactory returns on investment. Profitability ratios can be used to assess a company's success in generating profits and losses and its net returns relative to revenue, sales, or investment. These ratios evaluate the company's overall performance and the efficiency of management in generating adequate profits (Dutta et al., 2020; Nouralidokht, 2014). The profitability ratios were calculated as follows:

Profitability Ratios =

$$\begin{aligned}[&(\text{Gross Profit Margin} \times 0.028) + (\text{Operating Profit Margin} \times 0.032) + (\text{Net Profit Margin} \\ &\quad \times 0.033) + (\text{Return on Equity (ROE)} \times 0.049) + (\text{Return on Total Assets (ROA)} \\ &\quad \times 0.048) \\ &+(\text{Return on Current Assets} \times 0.018) + (\text{Return on Fixed Assets} \times 0.017) \\ &\quad + (\text{Earnings Before Interest and Taxes to Equity Ratio} \times 0.024) \\ &\quad + (\text{Gross Profit to Current Assets Ratio} \times 0.021)]\end{aligned}$$

3) Shareholders' Investment Ratios:

The shareholders' investment ratios were calculated as follows (Mazandaran et al., 2025):

Shareholders' Investment Ratios =

$$\begin{aligned}[&(\text{Earnings per Share (EPS)} \times 0.066) + (\text{Dividends per Share (DPS)} \times 0.054) \\ &\quad + (\text{Price-to-Earnings Ratio} \times 0.046) + (\text{Dividend Payout Ratio} \times 0.060) \\ &+(\text{Forecasted Earnings} \times 0.038) + (\text{Degree of Realization of Forecasted EPS} \times 0.037)]\end{aligned}$$

This structure presents the input and output variables used in the DEA-based financial performance evaluation framework. Let the activity group include $K_A$financial ratios $AR_1, \dots, AR_{K_A}$and let $w_k^{(A)}$denote the FAHP-derived normalized weight of the ratio $k$within this group ($\sum_{k=1}^{K_A} w_k^{(A)} = 1$). The composite activity input for DMU $j$in period $t$is constructed as:

$$X^t_{Activity,j} = \sum_{k=1}^{K_A} w_k^{(A)} \cdot AR^t_{k,j}$$

Similarly, composite indicators for the other groups are computed using their corresponding ratio sets and FAHP weights.

Proposed Model

In this section, the concept of the Malmquist Productivity Index is first introduced, followed by a presentation of its non-radial, non-oriented measurement approach. The Malmquist Productivity Index was introduced by Caves, Christensen, and Diewert (1982) and further developed within the DEA framework by Färe et al. (1994). The Malmquist Productivity Index evaluates the change in productivity of a decision-making unit (DMU) between two time periods. It is defined as the product of the efficiency change component and the Frontier shift / technical change component. The efficiency change (or catch-up effect) represents the extent to which a DMU improves or deteriorates its efficiency over time. In contrast, the Frontier shift / technical change (or technological change/innovation) reflects shifts in the efficient frontier between two time periods.

Notation and Production Technology

Decision-making units (DMUs) are indexed by $j = 1, \dots, n$.

Time periods are indexed by $t = 1, \dots, T$ (in this study $T = 4$ for 2013–2016).

Each DMU $j$in period $t$uses an input vector $x_j^t = (x_{1j}^t, \dots, x_{mj}^t) \in \mathbb{R}_+^m$to produce an output vector $y_j^t = (y_{1j}^t, \dots, y_{sj}^t) \in \mathbb{R}_+^s$.

Under variable returns to scale (VRS), the technology in the period $t$is defined as:

$$\mathcal{T}^t = \left\{ (x, y) \mid x \geq \sum_{j=1}^{n} \lambda_j\, x_j^t, y \leq \sum_{j=1}^{n} \lambda_j\, y_j^t, \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0 \right\}$$

The SBM distance (efficiency) of DMU $o$relative to technology $\mathcal{T}^t$is obtained by solving the SBM model described in Eqs. (10)–(11).

The efficiency change effect from period 1 to period 2 is measured using the following formula:

$$\text{Efficiency Change} = \frac{\text{Efficiency of } (x_0, y_0)^2 \text{ with respect to the period-2 frontier}}{\text{Efficiency of } (x_0, y_0)^1 \text{ with respect to the period-1 frontier}} \quad (1)$$

If the efficiency change is greater than 1, it indicates an improvement in relative efficiency from period 1 to period 2. An efficiency change of 1 indicates no change in efficiency, whereas a value less than 1 indicates a decline in efficiency. is determined by the distance of the measured efficiencies from their respective frontiers, a comprehensive evaluation of productivity change requires considering not only the efficiency change effect but also the Frontier shift/technical change (technological change or innovation) effect. In general, this can be expressed as follows:

$$\phi_1 = \frac{\text{Efficiency of } (x_0, y_0)^1 \text{ with respect to the period-1 frontier}}{\text{Efficiency of } (x_0, y_0)^1 \text{ with respect to the period-2 frontier}} \quad (2)$$

The numerator of Equation (2) already appears in Equation (1). The denominator of Equation (1) is measured as the efficiency score of $(\mathrm{x}_0, \mathrm{y}_0)^1$ with respect to the period-2 frontier. Similarly, the Frontier shift / technical change effect at $(\mathrm{x}_0, \mathrm{y}_0)^2$ is expressed as follows:

$$\phi_2 = \frac{\text{Efficiency of } (x_0, y_0)^2 \text{ with respect to the period-1 frontier}}{\text{Efficiency of } (x_0, y_0)^2 \text{ with respect to the period-2 frontier}} \quad (3)$$

Using ϕ_1 and ϕ_2, the frontier shift effect is defined as their geometric mean, that is:

$$\Delta\text{Frontier} = \phi = \sqrt{\phi_1 \cdot \phi_2} \quad (4)$$

If the Frontier shift / technical change (ϕ) is greater than 1, it indicates technological progress in the frontier around the DMU_0 from period 1 to period 2. A Frontier shift / technical change equal to 1 implies no change in the frontier (status quo), whereas a Frontier shift / technical change less than 1 indicates a decline in frontier technology. The Malmquist Productivity Index (MI) is defined as the product of the efficiency change and the Frontier shift / technical change, that is:

$$\text{Malmquist Productivity Index (MI)} = \text{Efficiency Change} \times \text{Frontier shift / technical change} \tag{5}$$

The first term represents the relative change in performance, while the second term reflects the relative change in the frontier used to evaluate this performance. Now, the numerical values for the efficiency of $(x_0, y_0)^{t_1}$ measured with respect to the period-t_2 frontier are developed as follows:

$$\delta^{t_2}((x_0, y_0)^{t_1})(t_1 = 1,2 \text{ and } t_2 = 1,2) \tag{6}$$

Using the above notation, the efficiency change (C) in Equation (1) can be expressed as follows:

$$C = \frac{\delta^2((x_0, y_0)^2)}{\delta^1((x_0, y_0)^1)} \tag{7}$$

The Frontier shift / technical change effect (F) in Equation (4) can be expressed as follows:

$$F = \left[\frac{\delta^1((x_0, y_0)^1)}{\delta^2((x_0, y_0)^1)} \cdot \frac{\delta^1((x_0, y_0)^2)}{\delta^2((x_0, y_0)^2)}\right]^{\frac{1}{2}} \tag{8}$$

To calculate the Malmquist Productivity Index (MI), the following formula represents the product of C and F is obtained:

$$MI = \left[\frac{\delta^1((x_0, y_0)^2)}{\delta^1((x_0, y_0)^1)} \cdot \frac{\delta^2((x_0, y_0)^2)}{\delta^2((x_0, y_0)^1)}\right]^{\frac{1}{2}} \tag{9}$$

To overcome the limitations of radial models, this study employs the non-radial, non-oriented Slack-Based Measure (SBM) of efficiency (Tone, 2001) and its super-efficiency extension (Tone, 2002). The final expression interprets the Malmquist Productivity Index (MI) as the geometric mean of two efficiency ratios: one reflecting efficiency change measured using the period-1 technology, and the other reflecting efficiency change measured using the period-2 technology. As observed from the formula, MI involves four terms: $\delta^1((x_0, y_0)^2)$، $\delta^2((x_0, y_0)^2)$، $\delta^1((x_0, y_0)^1)$ and

$\delta^2((x_0, y_0)^1)$. The first two terms are associated with within-period measurements (t = 1 or t = 2), while the latter two are for intertemporal comparison.

An MI value greater than 1 indicates an improvement in total factor productivity of DMU_0 from period 1 to period 2, whereas MI = 1 and MI < 1 represent no change and a decline in total factor productivity, respectively.

In the non-parametric framework, the Malmquist Index (MI) is constructed using DEA technologies. Several methods exist for calculating MI. Initially, Farrell, Grosskopf, Lindgren, and Roos (1989–1994) calculated MI using input- and output-oriented radial DEA models. Although the radial model has limitations, such as ignoring slack variables, MI can be calculated using a non-radial DEA model that incorporates slack variables and preserves the measurement nature. Alternatively, MI can also be computed using a non-radial, non-oriented DEA model.

In this study, the non-radial, non-oriented MI model under variable returns to scale is developed using Equations (10) and (11), which evaluate the efficiency of $(x_0, y_0)^t$(t = 1, 2) with respect to the evaluation set $(X, Y)^s$(s = 1, 2). To calculate the MI components, Equation (10) [SBM] is used. If feasible, the optimal value will not exceed 1. Otherwise, if infeasible, Equation (11) [Super SBM] is solved, which is always feasible and yields values greater than 1 in the non-oriented model.

$$
\begin{aligned}
&[\mathrm{SBM}]\delta^S((\mathbf{x_0}, \mathbf{y_0})^t) = \min_{\phi,\psi,\lambda} t - \frac{1}{m}\sum_{i=1}^{m} \Phi_i,\\
&t + \frac{1}{s}\sum_{r=1}^{s} \Psi_r = 1\\
&\sum_{j=1}^{n} x_{ij}^s \Lambda_j \le t x_{io}^t - \Phi_i x_{io}^t, \quad i = 1, \dots, m,\\
&\sum_{j=1}^{n} y_{rj}^s \Lambda_j \ge t y_{r0}^t + \Psi_r y_{r0}^t, \quad r = 1, \dots, s, \qquad\qquad (10)\\
&\sum_{j=1}^{n} \Lambda_j = t, \qquad\qquad j = 1, \dots, n,\\
&0 \le \Phi_i \le t, \quad (\forall_i),\\
&\Psi_r \ge 0, \quad (\forall_r),\\
&\Lambda_j \ge 0, \quad (\forall_j).
\end{aligned}
$$

$$
[\mathrm{Super\ SBM}]\delta^S((\mathbf{x_0}, \mathbf{y_0})^t) = \min_{\phi,\psi,\lambda} t + \frac{1}{m}\sum_{i=1}^{m} \Phi_i, \qquad (11)
$$

$$t - \frac{1}{s}\sum_{r=1}^{s} \Psi_r = 1$$
$$\sum_{j=1,\neq o}^{n} x_{ij}^{s}\,\Lambda_j \leq t x_{i0}^{t} + \Phi_i x_{i0}^{t}, \quad i = 1, \dots, m,$$
$$\sum_{j=1,\neq o}^{n} y_{rj}^{s}\,\Lambda_j \geq t y_{r0}^{t} - \Psi_r y_{r0}^{t}, \quad r = 1, \dots, s,$$
$$\sum_{j=1,\neq o}^{n} y_{rj}\,\Lambda_j = t, \qquad j = 1, \dots, n,$$
$$\Phi_i \geq 0, \qquad (\forall_i),$$
$$0 \leq \Psi_r \leq t, \quad (\forall_i),$$
$$\Lambda_j \geq 0, \qquad (\forall_j).$$

Results

In this study, the criteria for evaluating companies' financial performance were first selected by reviewing previous research conducted both domestically and internationally. Among these studies, the most frequently occurring criteria were identified. Subsequently, after consulting stock market experts, some of these criteria were removed, and additional criteria deemed important but less commonly used in previous research were included. In other words, the input and output criteria for this study were derived from a literature review and previous studies (summarized in Table 1 and the empirical background). They were further refined through group interviews with stock market experts.

For better data analysis, these criteria were ultimately categorized into six main groups. The criteria were weighted using a two-level fuzzy Analytic Hierarchy Process (FAHP). At the first level, the six main criteria were compared. Based on the results, shareholders' investment ratios were identified as the most important indicators. Following them, profitability ratios ranked second, and capital structure ratios ranked third. Liquidity ratios and activity ratios were ranked fourth and fifth, respectively, and production cost ratios were ranked sixth.

After evaluating and ranking the main criteria, the sub-criteria were prioritized separately at the second level. The score and ranking of each sub-criterion were obtained and are fully presented in the Research Variables section. The most important sub-criteria were earnings per share (EPS), dividend payout ratio, and dividends per share, which ranked first, second, and third, respectively. Accounts receivable turnover was ranked last among the sub-criteria.

Due to the extensive and standard nature of the FAHP method, the detailed weights of the main and sub-criteria, their ranking, and the calculation procedure are omitted in this article. Similarly, the actual values for the selected companies on each of the 38 criteria are not provided due to space constraints. These values cover five companies from three industries: automotive, basic metals, and mining, over the years 2013, 2014, 2015, and 2016. In this section, the companies' efficiency is evaluated for the years 2013 to 2016. Figure 1 clearly illustrates the efficiency scores of the companies Sebhan and Forous, which achieved the maximum efficiency score of 1 in all four years under review. The efficiency scores of the other companies are shown in columns 2, 3, 4, and 5 of Table 2.

Table 2. Efficiency Scores of Companies

Company	2013	2014	2015	2016
Khodro	0.1346	1.0000	1.0000	1.0000
Khavar	0.0630	0.0386	0.2227	0.0941
Khepars	0.0475	0.0139	0.1445	1.0000
Khesapa	0.1006	0.3724	0.4639	0.3103
Khakaveh	0.0384	0.1778	0.2009	0.1029
Folaj	0.2489	0.2381	0.5070	0.4725
Forous	1.0000	1.0000	1.0000	1.0000
Fekhas	0.2492	0.2402	1.0000	1.0000
Fekhouz	1.0000	0.6127	1.0000	1.0000
Foolad	0.2941	0.2301	0.6357	1.0000
Sebhan	1.0000	1.0000	1.0000	1.0000
Sarab	0.1894	0.1805	1.0000	1.0000
Sorood	0.2805	0.1587	1.0000	0.2817
Setran	0.2363	0.1848	0.2644	0.3356
Saroom	1.0000	0.3672	1.0000	0.4405

The results of the efficiency evaluation using Equation (10), i.e., the [SBM] model, are presented in Tables 2, 3, and 4. As observed in Tables 2, 3, and 4, the highest average efficiency (row 3 of Table 3) under the [SBM] model occurred in 2015, 2016, 2013, and 2014, respectively. Conversely, the lowest efficiency scores (row 2 of Table 3) for these four years correspond to 2014, 2013, 2016, and 2015, respectively.

Table 3. Company Efficiency Characteristics

Statistic	2013	2014	2015	2016
Minimum	0.0384	0.0139	0.1445	0.0941
Maximum	1.0000	1.0000	1.0000	1.0000
Mean	0.3922	0.3877	0.6959	0.6692
Median	0.2489	0.2381	1.0000	1.0000
Standard Deviation	0.3882	0.3471	0.3578	0.3787
Number of Efficient Units	4	3	8	8

Table 4. Industry Efficiency Results

Industry	2013	2014	2015	2016
Automotive	0.0768	0.3206	0.4064	0.5014
Basic Metals	0.5584	0.4642	0.8285	0.8945
Mining	0.5413	0.3782	0.8529	0.6116

Based on the results in Figures 1 and 2, the highest overall efficiency is in 2015, with average and median efficiencies of 0.696 and 1, respectively. Considering the median efficiency for this period, it can be inferred that more than half of the selected companies achieved the maximum efficiency score of 1. Similarly, for 2016, the median indicates that more than half of the companies again reached the maximum efficiency score.

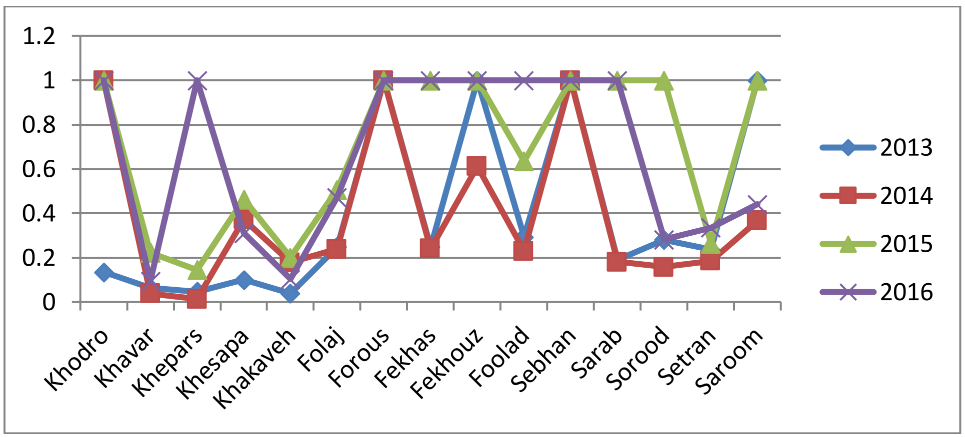

Figure 1. Results of Company Performance

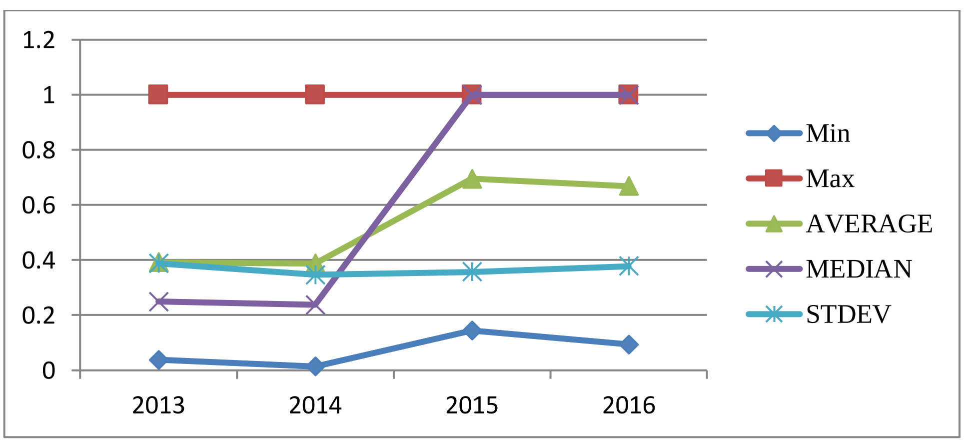

Figure 2. Company Performance Specifications

Finally, based on Figure 3, it can be concluded that the basic metals industry was more efficient than the mining and automotive industries, which ranked second and third, respectively. However, it is noteworthy that the automotive industry's efficiency showed an upward trend across all examined years, indicating relatively higher productivity growth than in the other two industries. This trend will be further analyzed in the following sections.

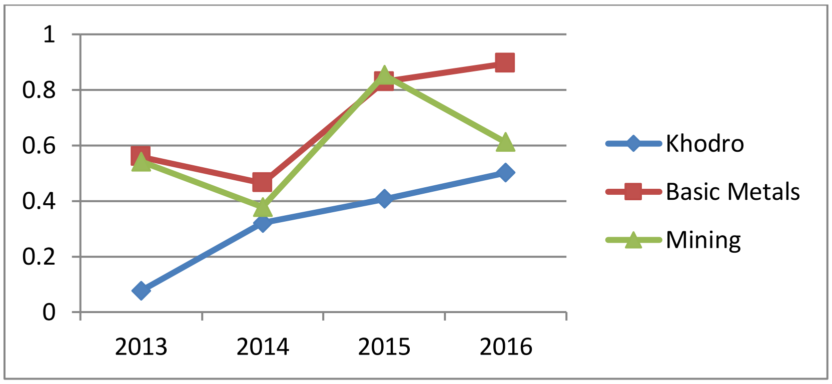

Figure 3. Industry Performance Results

To calculate the efficiency changes of firms/DMUs over time and the Malmquist index, four linear programming problems are first solved for each company, both within and between periods, using relation 10 or the [SBM] model. For the infeasible solutions of these four problems, four additional linear programming problems, within and between periods, are solved using relation 11 or the [Super-SBM] model, which is non-radial and without nature, as presented in the previous section. The results are presented in Table 5.

Table 5. Results of the Gradual Change Effect, Frontier shift / Technical change, and Malmquist Index

	Malmquist Index (MI)			Frontier shift / Technical change (F)			Gradual Change Effect (C)		
Company	(2015-2016)	(2014-2015)	(2013-2014)	(2015-2016)	(2014-2015)	(2013-2014)	(2015-2016)	(2014-2015)	(2013-2014)
Khodro	8825/0	6734/0	8282/5	1556/1	8213/1	1941/0	7637/0	3697/0	0214/30
Khavar	4207/0	6971/2	5450/0	9961/0	4680/0	8882/0	4224/0	7632/5	6137/0
Khepars	5692/8	1778/5	2799/0	2367/1	4993/0	9551/0	929/6	3712/10	2931/0
Khesapa	9583/0	8184/0	6224/2	4330/1	6569/0	7081/0	6687/0	2457/1	7033/3
Khakaveh	5293/0	8223/0	0435/4	0338/1	7276/0	8743/0	5120/0	1301/1	6249/4
Folaj	7314/0	2532/1	7716/0	7849/0	5884/0	8067/0	9319/0	1297/2	9565/0
Forous	8979/0	9162/0	0687/1	8899/0	9148/0	9441/0	0090/1	0015/1	1320/1
Fekhas	0085/1	4375/2	9177/0	9674/0	5303/0	9519/0	0425/1	5965/4	9641/0

Fekhouz	5931/1	0959/2	2149/0	5561/0	6178/0	5146/2	8648/2	3923/3	0855/0
Foolad	9190/1	3647/1	7343/0	2092/1	4941/0	9385/0	5870/1	7622/2	0.7825
Sebhan	0957/0	8471/0	9781/0	8496/0	3934/5	5057/0	1126/0	1571/0	9344/1
Sarab	0398/1	0587/2	9376/0	9809/0	3670/0	9840/0	0600/1	6097/5	9528/0
Sorood	4071/0	1854/2	5368/0	4478/1	3462/0	9487/0	2812/0	3120/6	5658/0
Setran	4083/1	7071/0	7313/0	1098/1	4941/0	9352/0	2689/1	4312/1	7820/0
Saroom	8145/0	8137/0	3201/0	8631/1	2966/0	8836/0	4372/0	7436/2	3623/0

In Figure 4, the productivity improvement of Khapars during the studied periods is clearly visible. The productivity improvements and regressions for the other units are shown in columns 8, 9, and 10 of Table 5. Furthermore, the gradual change (C) and boundary shift (T) are displayed in columns 2, 3, 4, 5, 6, and 7, respectively.

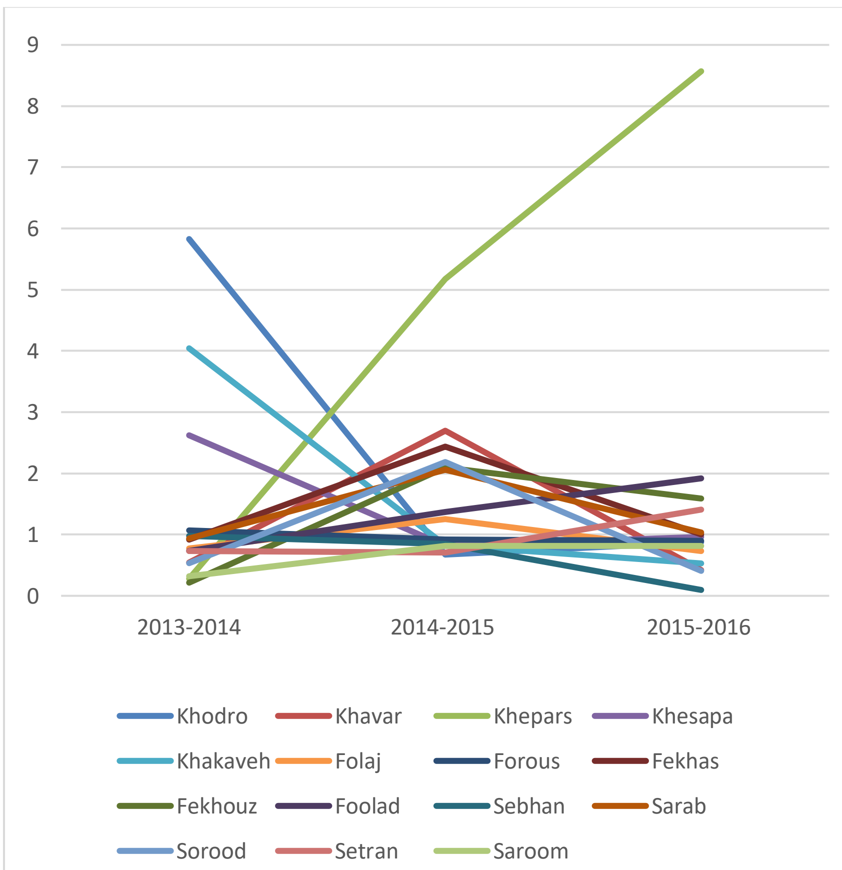

Figure 4. Company Productivity Results

As seen in Figure 5, the highest productivity improvement, based on the Malmquist index (MI), corresponds to the periods 2013-2014, 2014-2015, and 2015-2016 for the companies Khodro, Khapars, and Khapars, respectively. Additionally, the most significant productivity regression for these three periods corresponds to the units Fakhouz, Khodro, and Sabhan, respectively.

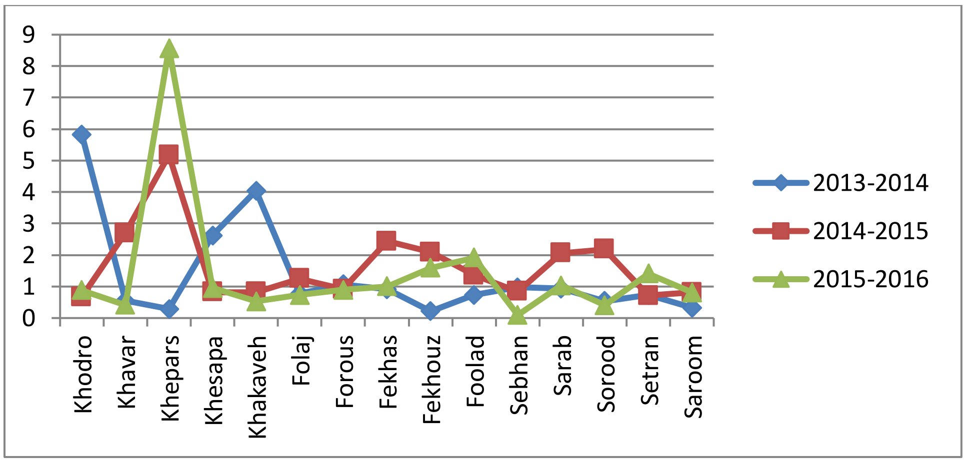

Figure 5. Company Productivity Results by Period

Based on the results in Table 6 and Figure 6, the highest productivity is observed during 2015-2016. The average and median productivity for this period are 1.66 and 1.25, respectively. Based on the median value for this period, more than half of the selected companies improved their productivity, and the period 2015-2016 was the best in terms of the productivity index.

Table 6. Specifications of Gradual Change Effect, Frontier shift / Technical change, and Malmquist Index

Period	2013-2014	2014-2015	2015-2016
Minimum	0.214938	0.6733529	0.0956851
Maximum	5.8281929	5.1778218	8.5691517
Mean	1.3686882	1.6578884	1.4183566
Median	0.7716249	1.2532406	0.8978645
Standard Deviation	1.5900848	1.1998448	2.0334766

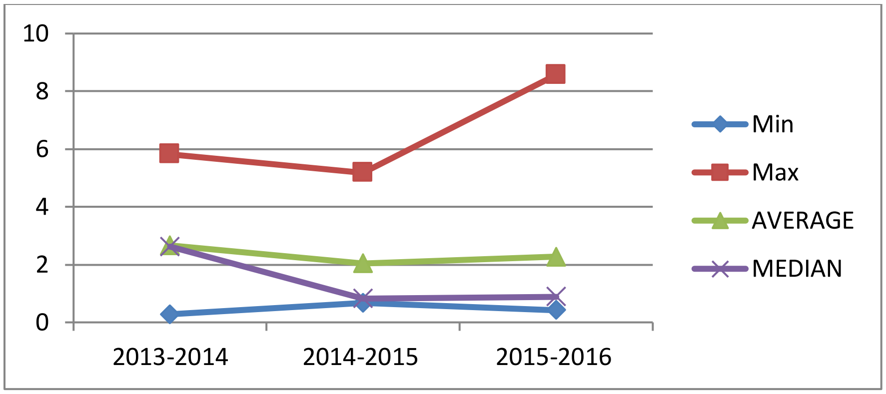

Figure 6. Company Productivity Specifications

Based on Table 7 and Figure 7, it can be concluded that only in the period 2015-2016 did all industries experience productivity improvements. Finally, according to Figure 7, the automotive industry has made greater productivity gains than the basic metals and mining industries, with the latter ranking second and third, respectively.

Table 7. Industry Productivity Results

Industry	2013-2014	2014-2015	2015-2016
Khodro	2.6638129	2.037778	2.2720115
Basic Metals	0.741469	1.6134926	1.229982
Mining	0.7007826	1.3223947	0.7530762

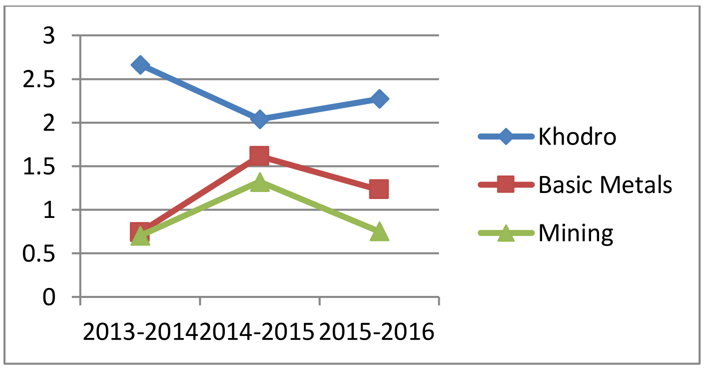

Figure 7. Industry Productivity Results

Benchmark Comparison / Robustness Check

To assess the robustness of the proposed hybrid framework, we performed two benchmark comparisons commonly used in the DEA–MPI literature: (i) the conventional radial BCC (VRS) DEA model for cross-sectional efficiency, and (ii) the conventional radial Malmquist productivity index for intertemporal productivity change. The benchmark models were implemented using the same DMUs and input–output structure, and rankings were compared at both the efficiency and productivity levels. The comparison shows that the overall ordering of firms is broadly consistent across models; however, noticeable rank shifts occur for DMUs with substantial input/output slacks. This is expected because the SBM framework explicitly accounts for non-proportional adjustments (slacks), which are common in financial ratios. Therefore, the proposed SBM-based Malmquist decomposition provides additional diagnostic insights by separating catch-up (EC) from frontier-shift (TC) effects while avoiding potential distortions associated with radial measures that ignore slacks.

Conclusion

This study was conducted to evaluate the financial performance of selected companies listed on the stock exchange using a combined approach of Data Envelopment Analysis (DEA) and the Malmquist index. Similar to Fazli and Mansouri (2007), Cai and Wu (2001), and Frey and Harker (1999), hierarchical analysis was employed as an indicator within DEA to measure financial performance. The distinction of this research lies in the use of the [SBM] model for efficiency evaluation. At the same time, a productivity assessment was conducted using a combination of DEA and the Malmquist index. The results of this study indicate that the highest average efficiency, based on the [SBM] model, occurred in 2015, 2016, 2013, and 2014. Conversely, the lowest efficiency for these four years corresponded to 2014, 2013, 2016, and 2015, respectively. The companies Sabhan and Foroush achieved the maximum efficiency score of one in all four years under review. Among industries, the basic metals industry demonstrated higher efficiency than the mining and automotive industries, with mining and automotive ranking second and third, respectively. However, in terms of productivity, the automotive industry made greater progress than the mining and basic metals industries, which ranked second and third, respectively. According to the findings, in almost all years, the symbol Sabhan in the mining industry, Khodro in the automotive industry, and Foroush in the basic metals industry ranked first. Therefore, it is recommended that investors consider these results when planning investments in these industries.

Theoretical Implications

This study strengthens the DEA-based financial performance literature by demonstrating that slack-aware (SBM) intertemporal measurement can alter productivity interpretations relative to radial formulations, and by providing an operational way to integrate expert judgment (FAHP) into DEA input/output construction without subjective weight assignment within the DEA model.

Practical Implications

For investors, MI-based rankings highlight firms with persistent productivity growth rather than only one-year efficiency. For managers, the decomposition into efficiency change vs. technical change indicates whether improvements should focus on internal operational/financial adjustments (catch-up) or broader capability/technology and market positioning (frontier shift).

Recommendations

The following suggestions are offered to improve the financial performance (efficiency and productivity) of companies and industries listed on the stock exchange, as well as to enhance the quality of future studies:

Investment managers and company executives can use the combined model presented in this study to analyze the financial performance of companies and industries on the Iranian stock exchange on a large scale for trading or forecasting financial performance.

Incorporate expert opinions and/or other productivity indicators, such as the Malmquist-Luenberger index, alongside the model proposed in this research.

Limitations and Future Research

Limitations include the restricted sample size and period (2013–2016) and the exclusion of undesirable outputs. Future work can extend the panel, apply the Malmquist–Luenberger index to undesirable outputs, and compare against additional ranking enhancers (e.g., DEA cross-efficiency or DEA–MCDM) and predictive models (e.g., ANN).

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

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Conflict of interest

The authors declare no conflict of interest.

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