Journal of Economic Cooperation and Development, 47, 2 (2026), 259-300

Using DEA for Evaluating Winner-Loser Investment Portfolios based on Intra-Firm Efficiency: Evidence from the Tehran Stock Exchange

Ali Moradi[1], Abdolmajid Abdolbaghi Ataabadi[2] and
Seyed Mohammad Hassan Hosseini[3]

ABSTRACT

This study employs Data Envelopment Analysis (DEA) to evaluate the performance of win-loss investment portfolios constructed based on the fundamental efficiency of internal corporate factors. Using a sample of 382 firms listed on the Tehran Stock Exchange from 2011 to 2023, we specify an input-oriented DEA model incorporating seven financial ratios as inputs—current ratio, debt ratio, accounts receivable turnover, total assets turnover, inventory turnover, fixed asset turnover, and inventory-to-working capital ratio—and seven profitability and valuation metrics as outputs—return on assets (ROA), return on equity (ROE), net profit margin, earnings per share (EPS), price-to-earnings ratio (P/E), operating profit margin, and Tobin's Q. Firms are classified into winner (high-efficiency) and loser (low-efficiency) portfolios within their respective industries. We then compare the future market performance of these portfolios using both parametric tests and stochastic dominance analysis across multiple investment horizons. The results reveal a nuanced relationship between fundamental efficiency and subsequent returns. The winner portfolio demonstrates statistically significant superiority over the loser portfolio for six-month raw returns, one-year raw returns, and one-year industry-adjusted returns. However, for six-month industry-adjusted returns, the winner portfolio significantly underperforms the loser portfolio. These findings suggest that while fundamentally efficient firms deliver superior long-term performance, short-term industry dynamics can temporarily overshadow firm-specific fundamentals. The results have important implications for portfolio management, particularly regarding the alignment of investment horizon with fundamental analysis signals.

[1] Department of Industrial Engineering and Management, Shahrood University of Technology, Shahrood, Iran. E-mail: mfbazad1357@yahoo.com
[2] Department of Industrial Engineering and Management, Shahrood University of Technology, Shahrood, Iran. E-mail: abdolbaghi@shahroodut.ac.ir
[3] Department of Industrial Engineering and Management, Shahrood University of Technology, Shahrood, Iran. E-mail: sh.hosseini@shahroodut.ac.ir

ملخص

تستخدم هذه الدراسة أسلوب تحليل مغلف البيانات (Data Envelopment Analysis - DEA) لتقييم أداء محافظ الاستثمار الرابحة والخاسرة التي يتم تكوينها استنادا إلى الكفاءة الأساسية للعوامل الداخلية للشركات. واعتمدت الدراسة على عينة تضم 382 شركة مدرجة في بورصة طهران خلال الفترة من 2011 إلى 2023،وقد تم تحديد نموذج DEA موجه نحو المدخلات (Input-Oriented DEA Model)، بحيث يتضمن سبع نسب مالية كمدخلات، وهي: نسبة التداول (Current Ratio)، ونسبة المديونية (Debt Ratio)، ومعدل دوران الحسابات المدينة (Accounts Receivable Turnover)، ومعدل دوران إجمالي الأصول (Total Assets Turnover)، ومعدل دوران المخزون (Inventory Turnover)، ومعدل دوران الأصول الثابتة (Turnover Fixed Asset)، ونسبة المخزون إلى رأس المال العامل (Ratio Inventory-to-Working Capital)، كما يتضمن النموذج سبعة مؤشرات للربحية والتقييم كمخرجات، وهي: العائد على الأصول (ROA)، والعائد على حقوق الملكية (ROE)، وهامش صافي الربح (Margin Net Profit)، وربحية السهم (EPS)، ونسبة السعر إلى الربحية (P/E)، وهامش الربح التشغيلي (Operating Profit Margin)، ومعامل توبن (Tobin's Q). وقد تم تصنيف الشركات إلى محافظ رابحة(عالية الكفاءة) ومحافظ خاسرة(منخفضة الكفاءة) داخل القطاعات الصناعية التي تنتمي إليها. بعد ذلك، تمت مقارنة الأداء السوقي المستقبلي لهذه المحافظ باستخدام كل من الاختبارات المعلمية (Parametric Tests) وتحليل السيادة العشوائية (Stochastic Dominance Analysis) عبر آفاق استثمارية متعددة. وتكشف النتائج عن وجود علاقة معقدة بين الكفاءة الأساسية والعوائد اللاحقة. فقد أظهرت المحفظة الرابحة تفوقا ذا دلالة إحصائية على المحفظة الخاسرة فيما يتعلق بالعوائد الخام لفترة ستة أشهر، والعوائد الخام لفترة سنة واحدة، والعوائد المعدلة حسب القطاع الصناعي لفترة سنة واحدة. ومع ذلك، بالنسبة للعوائد المعدلة حسب القطاع الصناعي لفترة ستة أشهر، حققت المحفظة الرابحة أداء أدنى بشكل معنوي مقارنة بالمحفظة الخاسرة. وتشير هذه النتائج إلى أنه على الرغم من أن الشركات ذات الكفاءة الأساسية المرتفعة تحقق أداء أفضل على المدى الطويل، فإن الديناميكيات قصيرة الأجل الخاصة بالقطاع الصناعي قد تطغى مؤقتا على العوامل الأساسية الخاصة بالشركات. وتحمل هذه النتائج دلالات مهمة لإدارة المحافظ الاستثمارية، ولا سيما فيما يتعلق بضرورة مواءمة الأفق الزمني للاستثمار مع الإشارات المستمدة من التحليل الأساسي للشركات.

RÉSUMÉ

Cette étude utilise l'analyse d'enveloppe des données (DEA) pour évaluer la performance de portefeuilles d'investissement « gagnants-perdants » construits sur la base de l'efficacité fondamentale des facteurs internes des entreprises. À partir d’un échantillon de 382 sociétés cotées à la Bourse de Téhéran entre 2011 et 2023, nous définissons un modèle DEA axé sur les intrants, intégrant sept ratios financiers comme intrants — ratio de liquidité générale, ratio d'endettement, rotation des créances clients, rotation de l'actif total, rotation des stocks, rotation des immobilisations et ratio stocks/fonds de roulement — et sept indicateurs de rentabilité et de valorisation comme sorties — rendement des actifs (ROA), rendement des capitaux propres (ROE), marge bénéficiaire nette, bénéfice par action (BPA), ratio cours/bénéfice (P/E), marge bénéficiaire d'exploitation et Q de Tobin. Les entreprises sont classées en portefeuilles « gagnants » (haute efficacité) et « perdants » (faible efficacité) au sein de leurs secteurs respectifs. Nous comparons ensuite la performance future de ces portefeuilles sur le marché à l’aide de tests paramétriques et d’une analyse de dominance stochastique sur plusieurs horizons d’investissement. Les résultats révèlent une relation nuancée entre l’efficacité fondamentale et les rendements ultérieurs. Le portefeuille des gagnants affiche une supériorité statistiquement significative par rapport au portefeuille des perdants pour les rendements bruts sur six mois, les rendements bruts sur un an et les rendements ajustés au secteur sur un an. Cependant, pour les rendements ajustés au secteur sur six mois, le portefeuille des gagnants sous-performe significativement par rapport au portefeuille des perdants. Ces résultats suggèrent que, si les entreprises fondamentalement efficaces affichent des performances supérieures à long terme, la dynamique sectorielle à court terme peut temporairement éclipser les fondamentaux propres à l’entreprise. Ces résultats ont des implications importantes pour la gestion de portefeuille, notamment en ce qui concerne l’alignement de l’horizon d’investissement sur les signaux de l’analyse fondamentale.

Keywords: Data Envelopment Analysis, Intra-Firm Efficiency, Investment, Portfolio Performance,

JEL Classification: C81, G14,G11

1. Introduction

In today's high-risk investment environment, achieving optimal returns while simultaneously mitigating risk remains a persistent challenge for market participants. Investors continuously seek the optimal combination of financial assets to maximize expected returns for a given level of risk, a foundational principle established by modern portfolio theory (Markowitz, 1952). Central to this endeavor is the determination of securities' intrinsic value through fundamental analysis, which examines economic, industry, and firm-specific factors to identify mispriced assets (Senfi & Sheikh, 2024). The primary objective of fundamental analysis is to estimate the intrinsic value of securities and compare it with prevailing market prices to inform investment decisions. Return represents the compensation an investor receives for committing capital over an investment period, while risk reflects the uncertainty surrounding the success of that financial commitment (Roncalli, 2020). Portfolio diversification through strategic asset allocation has emerged as a primary mechanism for managing this uncertainty, positioning portfolio construction as a cornerstone of modern financial decision-making (Wang et al., 2023; Hasanah et al., 2025).

The extant literature conceptualizes the investment problem as encompassing two distinct but interrelated challenges. The first is stock selection, which involves comprehensive analysis of alternative assets—including industry prospects, corporate financial health, historical performance trajectories, and prevailing market conditions—to identify securities warranting inclusion in the investment universe. The second challenge is investment weighting, which is formally structured as an optimization (or multi-criteria decision-making) problem. This stage aims to determine optimal capital allocation across selected assets to either minimize portfolio risk for a specified expected return or maximize expected return for a given level of portfolio risk (Zhou et al., 2021).

Investors use different evaluation tools and methods to overcome the complex risks of the capital market. One of these tools is fundamental analysis, which focuses on evaluating internal market factors to make informed decisions (Majeed et al., 2025). These tools enable investors to reduce risks and optimize returns by considering the internal factors that drive market dynamics. Fundamental analysis involves reviewing economic, industry, and intra-firm factors to determine the true value of a publicly traded company's stock. This analysis tackles macroeconomic conditions such as interest rates and unemployment to assess their impact on the stock market (Singh et al., 2021).

Many stock investment strategies require holding both long and short positions based on the performance of winning and losing stocks. It is expected that stocks with strong fundamentals will perform better than stocks with weak fundamentals in the future. However, external fundamental factors and non-fundamental factors can affect the market reaction. The determination of winner-loser stocks is based on the correlation of past and future performance. Many evidences show that past good performances are repeated in the short-term future, but in the long-term periods, the reverse behavior is observed in the price trend (Külpmann, Mathias, 2004).

There are various methods for evaluating the performance of companies by investigating and integrating their internal factors. Data Envelopment Analysis (DEA) is a well-known effective method in operational and financial research to estimate frontiers and estimate efficiency (Zhou et al., 2021). Portfolios need to be evaluated based on several aspects, and so, the input-output procedures are used to provide the characteristics of multiple inputs and multiple outputs. Therefore, the DEA method, as a data-driven evaluation approach based on multiple input and output indicators, is increasingly used in performance evaluation, including for evaluating stocks and portfolios. As is evident in the literature, the required input and output indicators are usually derived from the financial data of listed companies (Zhou et al., 2021). This approach uses the input and output factors of the units to classify them into two efficient and inefficient groups (Shabbir and Muhammad, 2019).

This article aims to evaluate the performance of win-loss investment portfolios at Tehran Security Exchange (TSE) based on intra-firm efficiency using fundamental variables in periods from 2011 to 2022. The market performance of these portfolios is also compared with each other. The evaluation of fundamental indicators. An efficient portfolio is expected to have a higher market performance than an inefficient portfolio, which means that the market will give more importance to intra-firm fundamentals in achieving desirable results. Identified stocks will be evaluated to find the effectiveness of these internal factors in identifying effective stocks and the performance of these selected stocks. In addition, to investigate companies' stock, the internal factors of companies are considered to use in the DEA approach.

Using the Tehran Stock Exchange as a case study for an emerging market facing unique economic conditions, this study adopts and utilizes the Data Envelopment Analysis (DEA) procedure to evaluate the performance of winner-loser investment portfolios based on intra-firm efficiency. The research incorporates current ratio, debt ratio, accounts receivable turnover, total assets turnover, inventory turnover, fixed asset turnover, and the ratio of inventory to working capital as model inputs. Additionally, the model calculates ROA, ROE, net profit margin, EPS, P/E, operating income, and Tobin's Q as outputs. The future performance of winner-loser portfolios is evaluated using the stochastic dominance method. The statistical sample includes 382 companies admitted to the Tehran Stock Exchange during the period from 2011 to 2023. This research contributes to the existing literature by providing empirical evidence from an emerging market context, where unique institutional and economic factors may influence the relationship between fundamental efficiency and subsequent stock returns. In this way, the contribution of the study is presented as threefold:

- *Methodological:* the application of a comprehensive, theoretically-grounded DEA model to a novel and challenging dataset from the Tehran Stock Exchange.
- *Contextual:* providing rare empirical evidence on the efficiency-performance relationship within a highly volatile, sanction-impacted emerging market.
- *Nuanced Empirical Finding:* the discovery and analysis of a significant short-term contradiction where efficient portfolios underperform on an industry-adjusted basis. This finding adds complexity to the standard narrative and opens new avenues for research into the interaction of market microstructure, investor behavior, and fundamental efficiency in such markets.

The rest of this work is organized as follows. Section 2 investigates the works related to this study and seeks methods and information on how to evaluate the performance of portfolios. Section 3 provides the method and materials of the research as well as the research procedure. Section 4 presents the results along with the implications of the findings. Finally, conclusions, limitations, and suggestions for future research are presented in Section 5.

2. Literature Review

Investment is traditionally defined as the "commitment of resources to achieve later benefits" in the related literature. If an investment involves money, it is usually defined as a "commitment of money to receive more money later". The main purpose of investment is to exploit capital and increase wealth, and invest in different economic areas. This process is mainly used in raising personal capital, financial future, or business goals.

In any case, investment is usually accompanied by needs and requires careful analysis of market conditions, evaluation, and possible returns, and considering financial and time issues (Bodie et al., 2021). Due to the existence of various risks, including market risk (Hull, 2003), interest rate risk (Roncalli, 2020), inflation risk (Bekaert, & Wang, 2010), and operational risk (Roncalli, 2020), people and companies prefer to form a portfolio instead of investing in one area. In this way, Fundamental Analysis (FA) that investigates firms' financials and operations, including sales, earnings, growth potential, assets, debt, management, products, and competition, plays a vital role in making portfolio decisions. FA may also include analyzing market behavior that stresses the study of the underlying factors of supply and demand. However, due to the capital market constraint, the market often cannot reflect relevant fundamental information instantaneously. Some empirical evidence shows that the twelve fundamental financial signals presented by Lev and Thiagarajan (1993) can explain or even predict future changes in earnings as well as revisions in analysts' forecasts. (Abarbanell and Bushee 1997).

Prior research was continued by Piotroski (2000), who used an investment strategy based on nine accounting-based signals that can generate abnormal returns. The investment strategy is to long expected winners and short expected losers, wherein the FSCORE is applied as a proper filter in forming the portfolio of high book-to-market (BM) stocks. Afterwards, Mohanram (2005) proposed a GSCORE to indicate the long-expected winners and short-expected losers in forming the portfolio of low BM stocks. Another related effort showed that a high FSCORE can generate a higher return than a medium FSCORE based on Eurozone stocks in 1999–2010 (Mohr, 2012).

On the other hand, some researchers prefer financial statement analysis in predicting future realizations of both earnings and returns. For instance, Ou and Penman (1989) show that certain financial ratios can be useful in predicting future changes in earnings. Similarly, Abarbanell and Bushee (1997) developed an investment strategy based on these signals and demonstrated that this approach can earn significant abnormal returns. Based on the results of many studies, fundamental analysis is used by applying a set of steps and rules in determining the intrinsic value of stocks based on the prediction of expected economic variables affecting the performance of businesses. The assessment of financial strength of companies, management efficiency, and business opportunities is based on the analysis of historical financial information and the current conditions of companies (Fontanills & Gentile, 2002; and Thomsett, 2006).

Many efforts have focused on forming/evaluating portfolios by identifying winners and losers based on information in the financial statements. The related literature shows that financial statement analysis is very efficient in differentiating between ex-post winners and losers (Mohanram, 2005). For instance, Beneish et al. (2001) highlighted the usefulness of contextual fundamental analysis in predicting extreme stock returns. They proposed a two-stage procedure to identify winners and losers. First, they defined the context for analysis by identifying extreme performers, and then, they developed a context-specific forecasting model to separate winners from losers.

Table 1 demonstrates characteristics of studies conducted in the evaluation of portfolios using the DEA technique based on fundamental data. As the table shows, in previous research, the focus has generally been on introducing new versions of DEA techniques for portfolio evaluation. In addition, some of them have evaluated the efficiency of limited stock without providing any effective strategies for investment. This is the first study that proposed a proper procedure considering the efficiency of a wide range of companies using comparison of indicators based on industry software, efficient and inefficient companies in each industry. In addition, to do a comprehensive evaluation, the behavior of the momentum of the future return of the Winner-Loser stock is investigated.

The selection of appropriate financial ratios as proxies for fundamental efficiency requires careful theoretical grounding in both the corporate finance and production economics literatures. In the context of DEA-based portfolio analysis, input variables should represent resources or factors that firms employ in their operations, while output variables should capture the outcomes or value generated from these resource deployments. The seven input variables selected in this study, current ratio, debt ratio, accounts receivable turnover, total assets turnover, inventory turnover, fixed asset turnover, and inventory-to-working capital ratio, are theoretically anchored in three distinct dimensions of corporate operations: liquidity management, capital structure decisions, and operational efficiency.

Liquidity metrics, including the current ratio and inventory-to-working capital ratio, reflect the firm's ability to meet short-term obligations and manage working capital effectively. According to the theoretical framework of working capital management, optimal liquidity positions enable firms to avoid financial distress while minimizing idle resources. Capital structure theory, particularly the trade-off theory and pecking order theory, justifies the inclusion of the debt ratio as an input, as leverage decisions influence both the cost of capital and financial flexibility. Operational efficiency metrics—accounts receivable turnover, total assets turnover, inventory turnover, and fixed asset turnover—capture how effectively management utilizes specific asset categories to generate revenue, drawing directly from the theoretical literature on asset utilization and productivity analysis.

The output variables—ROA, ROE, net profit margin, EPS, P/E, operating profit margin, and Tobin's Q—represent both accounting-based and market-based measures of firm performance. Return on Assets (ROA) and Return on Equity (ROE) are grounded in DuPont analysis and the theoretical literature on profitability measurement, capturing how effectively firms generate returns from their asset base and shareholder investments. Net profit margin and operating profit margin reflect pricing power and cost management capabilities, central themes in industrial organization and strategic management literatures. Earnings per Share (EPS) and Price-to-Earnings (P/E) ratio connect accounting performance to shareholder value creation, drawing on valuation theory. Tobin's Q, perhaps the most theoretically robust output measure, captures the market's assessment of firm value relative to asset replacement costs, integrating both current profitability and future growth expectations.

The comprehensive nature of these fourteen variables addresses the multidimensionality of fundamental efficiency. As demonstrated in Table 1, this variable set synthesizes and extends previous DEA-based portfolio studies. Roslah Arsad et al. (2017), Lim et al. (2014), and Jothimani et al. (2017) employed similar combinations of liquidity, leverage, turnover, and profitability metrics, though no single prior study has integrated all seven inputs and seven outputs simultaneously. Our selection thus represents a theoretically comprehensive approach to measuring fundamental efficiency, capturing the resource-based view's emphasis on heterogeneous firm capabilities while maintaining comparability with the existing literature.

While traditional fundamental analysis and frontier methods like DEA remain valuable, the last five years have witnessed a paradigm shift in financial economics with the widespread adoption of Machine Learning (ML) techniques. These methods are increasingly used to predict stock returns, construct portfolios, and model complex, non-linear relationships that traditional models often miss. The literature has moved beyond simple comparisons, now focusing on hybrid models that integrate ML with classical approaches and on understanding how design choices impact model performance.

A seminal benchmark in this area is the work of Gu et al., (2020), which comprehensively demonstrated that ML methods like neural networks, gradient boosted trees, and random forests decisively outperform traditional linear regression models in predicting the cross-section of U.S. stock returns. This finding has been validated and extended across different geographical markets. For instance, Breitung (2023) applied a random forest model to an international dataset of liquid stocks, showing that portfolios based on the model's "outperformance probability" achieved significant alphas and Sharpe ratios, with the added benefit of being less prone to recommending highly volatile, small-cap stocks. The integration of ML with portfolio optimization frameworks has led to powerful hybrid methodologies. A common two-stage approach involves using ML algorithms for stock pre-selection, followed by a classical optimization model. Kumbure, et al., (2023) implemented this by using regression algorithms—including Random Forest, XGBoost, and Support Vector Regression (SVR)—to forecast stock values, and then employing a Mean-Value-at-Risk (VaR) model for the final portfolio selection. Their findings indicate that the hybrid model with AdaBoost prediction performed best across multiple international stock exchanges.

Recent review papers synthesize these advancements and offer critical perspectives. Caner and Fan (2025) provide a practitioner-focused guide, emphasizing that the choice of the ML technique must be made jointly with the portfolio objective function (e.g., maximum Sharpe ratio, global minimum variance) to be effective.

It should be noted that, while machine learning models offer powerful predictive capabilities, they often function as 'black boxes,' lacking the interpretability of DEA. Our approach prioritizes a transparent, theory-driven evaluation of fundamental efficiency, providing clear insights into the specific input-output drivers of performance, which is a key advantage for investors seeking to understand the 'why' behind a stock's potential.

Table 1: Characteristics of Investment Portfolio Performance Evaluation Studies Using DEA

Ref.	Input criteria										Output criteria												Research community	Methodology
	Current ratio	Quick ratio	Debt ratio	Debt to equity ratio	Solvency ratio-II	Receivables Turnover		Asset Turnover	Fixed Assets Turnover	Inventory Turnover	Price to book ratio	ROA	ROE	Net profit margin	Profit margin	EPS	P/E	Operating profit	Cash ratio	Tobin's Q Ratio	Inventory/working	p/s		
Roslah Arsad et al. (2017)				*			*				*	*	*		*	*	*						Malaysian stock market	DEA-CCR and DEA-BCC
Karimi & barati (2018)	*		*			*	*		*		*	*	*		*	*			*				Tehran Stock Exchange	Negative DEA
Kara & Çetinkaya (2022)	*		*								*	*							*				transportation and storage sector companies in the BIST	Output-Oriented CCR-O Analysis Model
Arasu et al. (2021)	*	*		*			*			*	*	*	*		*								National Stock Exchange	DEA-CCR and DEA-BCC
Peykani et al. (2022)					*	*						*		*				*					Tehran stock exchange	DEA–Shannon entropy
Ebrahimi & Hajizadeh (2021)	*	*	*				*		*			*			*								Tehran stock exchange	DEA hybrid with a new algorithm
Salimi & Shahriari (2023)			*				*	*			*	*											Tehran Stock Exchange	Input-oriented BCC Model
Lim et al. (2014)	*	*	*	*		*	*		*		*	*	*		*								Korean stock market	DEA cross-efficiency
Jothimani et al. (2017)	*	*	*	*		*	*		*	*	*	*	*		*	*							Indian stock market	PCA-DEA model
This study	*		*			*	*	*	*		*	*	*		*	*	*		*	*		*	Tehran Security Exchange	Input-oriented DEA

3. Data and Methodology

Data envelopment analysis (DEA) is a nonparametric method for measuring the relative efficiencies of a set of decision-making units (DMUs) that uses multiple inputs to produce multiple outputs to segment DMUs into efficient and inefficient groups. In nonparametric models, the structure of the model is not predetermined, and it is formed according to the existing data. Therefore, nonparametric methods need few assumptions about the data distribution from which the sample is investigated.

Farrell (1957) expressed the efficiency formula as follows:

Suppose we have a population consisting of n production units (firms) as $DMU_1, DMU_2, \dots, DMU_n$.we will have an input and output matrix as $x_j = (x_{1j}, x_{2j}, \dots, x_{mj})$ and $y_j = (y_{1j}, y_{2j}, \dots, y_{sj})$ respectively for DMU_j $(j = 1,2, \dots, n)$. The purpose is to evaluate the efficiency of DMU_k wherein $x_k = (x_{1k}, x_{2k}, \dots, x_{mk})$ and $y_k = (y_{1k}, y_{2k}, \dots, y_{sk})$ are input and output vectors of $DMU_{k,}$ respectively. The productivity of this unit is calculated as (1).

$$\text{Efficiency rate of unit k} = \frac{\sum_{r=1}^{s} u_r\, y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \qquad (1)$$

Where, v_i $(i = 1,2, \dots, m)$ are the weights assigned to the i*th* input and u_r $(r = 1,2, \dots, s)$ are the weights assigned to the r*th* output (Cooper et al., 2007).

Charnes et al. (1978) suggested that the efficiency, z, of a DMU_k decision unit can be determined by solving the model below (the so-called CCR model).

$$Max\ z = \frac{\sum_{r=1}^{s} u_r\, y_{rk}}{\sum_{i=1}^{m} v_i\, x_{ik}}\ ;\ k \in (1,2, \dots n)$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{i=1}^{m} v_i\, x_{ij}} \le 1\ ;\ (j = 1,2, \dots, n)$$

$$u_r \ \ge \varepsilon > 0\ ;\ r = 1,2, \dots, s$$

$$v_i \ \ge \varepsilon > 0\ ;\ \ i = 1,2, \dots, m$$

$$\varepsilon \in (10^{-6}, 10^{-8})$$

The model evaluates n decision maker units (DMUs), where each DMU takes m different inputs to produce s different outputs. In this model, $x_{ij}, y_{rj} > 0$ indicate inputs and outputs of unit $\mathrm{DMU}_{j,}$ respectively. In addition, z shows the efficiency of unit DMU_k. The nature of the DEA model lies in measuring the efficiency of a production unit of DMUs in maximizing its efficiency rate. However, the efficiency ratio of "virtual output" versus "virtual input" shall not exceed 1 for any DMU. The purpose is to obtain the ratio of weighted output divided by weighted input. According to the constraints, the optimal value of the objective function z is maximum, equal to 1. Therefore, DMU_k is known as an efficient unit if $z = 1$and so, there is at least one $u^*, v^* > 0$. Models of CCR are categorized as input-oriented and output-oriented (Cooper et al., 2007).

Table 2: Two Models of CCR

The input-oriented of CCR	**The output-oriented of CCR**
$max\ z = \sum_{r=1}^{s} u_r y_{rk}\ ;\ k \in (1,2, \dots n)$ Subject to: $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0\ ;\ (j = 1,2, \dots, n)$ $\sum_{i=1}^{m} v_i x_{ik} = 1\ ;\ k \in (1,2, \dots n)$ $u_r \geq \varepsilon > 0\ ;\ r = 1,2, \dots, s$ $v_i \geq \varepsilon > 0\ ;\ i = 1,2, \dots, m$ $\varepsilon \in (10^{-6}, 10^{-8})$	$min\ z = \sum_{i=1}^{m} v_i x_{ik}\ ;\ k \in (1,2, \dots n)$ Subject to: $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0\ ;\ (j = 1,2, \dots, n)$ $\sum_{r=1}^{s} u_r y_{rk} = 1\ ;\ k \in (1,2, \dots n)$ $u_r \geq \varepsilon > 0\ ;\ r = 1,2, \dots, s$ $v_i \geq \varepsilon > 0\ ;\ r = 1,2, \dots, m$ $\varepsilon \in (10^{-6}, 10^{-8})$

The input-oriented model is one of the most common models of DEA, which focuses on evaluating the efficiency of DMUs in using their input resources to produce a given level of outputs while comparing them with a reference DMU. As a result, this model assumes that inefficient units can become efficient if they reduce their input while maintaining the same level of production.

The output-oriented model supposes that inefficient units can become efficient if they increase their output while maintaining the same level of input. In other words, this model tries to find out how to improve the output characteristics of the respective unit to make it more efficient.

Table 2 represents the two abovementioned models of CCR through the mathematical model. This research uses the input-oriented CCR model because companies do not have much control over the amount of output (profit), but they can reduce their input and thus increase efficiency.

3.1. Research input and output variables

After reviewing the existing relevant studies, a set of appropriate financial variables was considered as input and output variables extracted from the existing literature, as shown in Tables 3 and 4. The seven input as well as the seven output variables were selected based on their theoretical roles in the firm's production function and value creation process: these fourteen variables provide a theoretically comprehensive measurement framework for fundamental efficiency.

The input variables capture the resource base available to management across liquidity, leverage, and operational dimensions. The output variables capture the outcomes achieved from these resources across accounting profitability, market valuation, and shareholder return dimensions. This input-output framework parallels the production function concept in microeconomic theory, where firms combine multiple inputs to produce valuable outputs. By encompassing both short-term operational metrics (turnover ratios, profit margins) and longer-term structural indicators (debt ratio, Tobin's Q), the model captures efficiency across multiple time horizons. This multidimensional approach is essential because fundamental efficiency is inherently multifaceted—a firm may excel in operational efficiency while maintaining suboptimal capital structure, or generate strong accounting profits while receiving low market valuations due to poor growth prospects. The DEA methodology's strength lies in its ability to accommodate this multidimensionality without requiring arbitrary weighting schemes, allowing the data to reveal which firms achieve the best combinations of input minimization and output maximization.

Table 3: Input Variables of the DEA Model

Variable	Measurement	Reference
Current Ratio	$\frac{Current\ Assets}{Current\ Liabilities}$	Edirisinghe & Zhang (2008), Lim et al (2014), Peykani et al (2022), Kara & Çetinkaya (2022), Arasu et al (2021), Ebrahimi & Hajizadeh (2021), Jothimani et al (2017), Topal et al (2013), Ling & Kamil (2010)
Debt Ratio	$\frac{Total\ Debt}{Total\ Assets}$	Salimi & Shahriari (2023), Kara & Çetinkaya (2022), Jothimani et al (2017), Peykani et al (2022), Ebrahimi & Hajizadeh (2021), Topal et al (2013)
Accounts Receivable Turnover Ratio	$\frac{Net\ Credit\ Sales}{Average\ Accounts\ Receivable}$	Peykani et al (2022), Jothimani et al (2017), Öztop & Uçak (2017)
Assets Turnover Ratio	$\frac{Net\ Sales}{Average\ Total\ Assets}$	Öztop & Uçak (2017), Arsad et al (2022), Arasu et al (2021), Ebrahimi & Hajizadeh (2021), Jothimani et al (2017), Lim et al (2014), Edirisinghe & Zhang (2008)
Inventory Turnover Ratio	$\frac{Cost\ Of\ Goods\ Sold}{Average\ Inventory}$	Öztop & Uçak (2017), Ebrahimi & Hajizadeh (2021), Herman (2018), Jothimani et al (2017), Lim et al (2014), Edirisinghe & Zhang (2008)
Fixed Assets Turnover Ratio	$\frac{Net\ Sales}{Average\ Fixed\ Assets}$	This study
Inventory To Working Capital Ratio	$\frac{Inventory}{Working\ Capital}$	This study

Table 4: Output Variables of DEA Model

Variable	Measurement	Reference
ROA	$\frac{Net\ Income}{Average\ Assets}$	Salimi & Shahriari (2023), Kara & Çetinkaya (2022), Arsad et al (2022), Peykani et al (2022), Arasu et al (2021), Jothimani et al (2017), Lim et al (2014), Topal et al (2013), Edirisinghe & Zhang (2008)
ROE	$\frac{Net\ Income}{Shareholders\ Equity}$	Salimi & Shahriari (2023), Kara & Çetinkaya (2022), Arsad et al (2022), Peykani et al (2022), Peykani et al (2022), Arasu et al (2021), Ebrahimi & Hajizadeh (2021), Jothimani et al (2017), Lim et al (2014), Topal et al (2013), Edirisinghe & Zhang (2008)
Net Profit Margin	$\frac{Net\ Profit}{Revenue}$	Öztop & Uçak (2017), Arsad et al (2022), Arasu et al (2021), Jothimani et al (2017), Lim et al (2014), Edirisinghe & Zhang (2008)
EPS	$\frac{Net\ Income\ -\ Preferred\ Dividends}{Weighted\ Average\ Shares\ Outstanding}$	Arsad et al (2022), Arasu et al (2021), Ebrahimi & Hajizadeh (2021), Jothimani et al (2017), Lim et al (2014), Edirisinghe & Zhang (2008)
P/E	$\frac{Share\ Price}{Earning\ Per\ Share}$	Arsad et al (2022), Jothimani et al (2017), Edirisinghe & Zhang (2008)
Operating Profit Margin	$\frac{Operating\ Profit}{Total\ Revenue}$	Arsad et al (2022), Öztop & Uçak (2017)
Tobin's Q Ratio	$\frac{\text{(Equity Market Value Total Liabilities)}}{\text{Total Assets}}$	Kara & Çetinkaya (2022), Kahveci, E & Taliyev (2016)

According to the considered objective of the research, the return variable is calculated as a continuous compound return as follows:

$$\mathrm{R_{it}} = ln\frac{p_{it} + D_{it}}{p_{it-1}}$$
$$adjR_{it} = R_{it} - R_{industry}$$
$$RP_{winner} = \sum_{i=1}^{n} w_i R_i$$
$$RP_{loser} = \sum_{i=1}^{n} w_i R_i$$

Where, R_i is the stock return, p_{it} shows the stock price during the period t, D_{it} indicates the stock dividends in the period t, $R_{industry}$ refers to the weighted average industry efficiency, RP is the stock return of the winner or loser, and w_i shows the weight of stocks in the portfolio.

3.2. Research procedure

The procedure of the current research includes identifying and evaluating the fundamental factors and evaluating the efficiency of companies based on these factors using the DEA approach, to form effective and ineffective portfolios. This procedure is shown in more detail in Figure 1 and the following explanations.

The required data, including input and output variables of companies listed on the Tehran Stock Exchange from 2011 to 2012, were obtained from the www.tse.ir database. In addition, in the stage of data screening, the industries whose number of companies was less than 5 or had incomplete information were eliminated. The final list of tested industries and excluded industries is given in Table 5. It is worth mentioning that the evaluation of the performance of the winner-loser portfolio is done by considering the periods of 6 and 12 months. After data screening according to Table 5, a total of 382 companies from different industries were identified as a proper sample of eligible companies to conduct the test.

Figure 1: Research Procedure

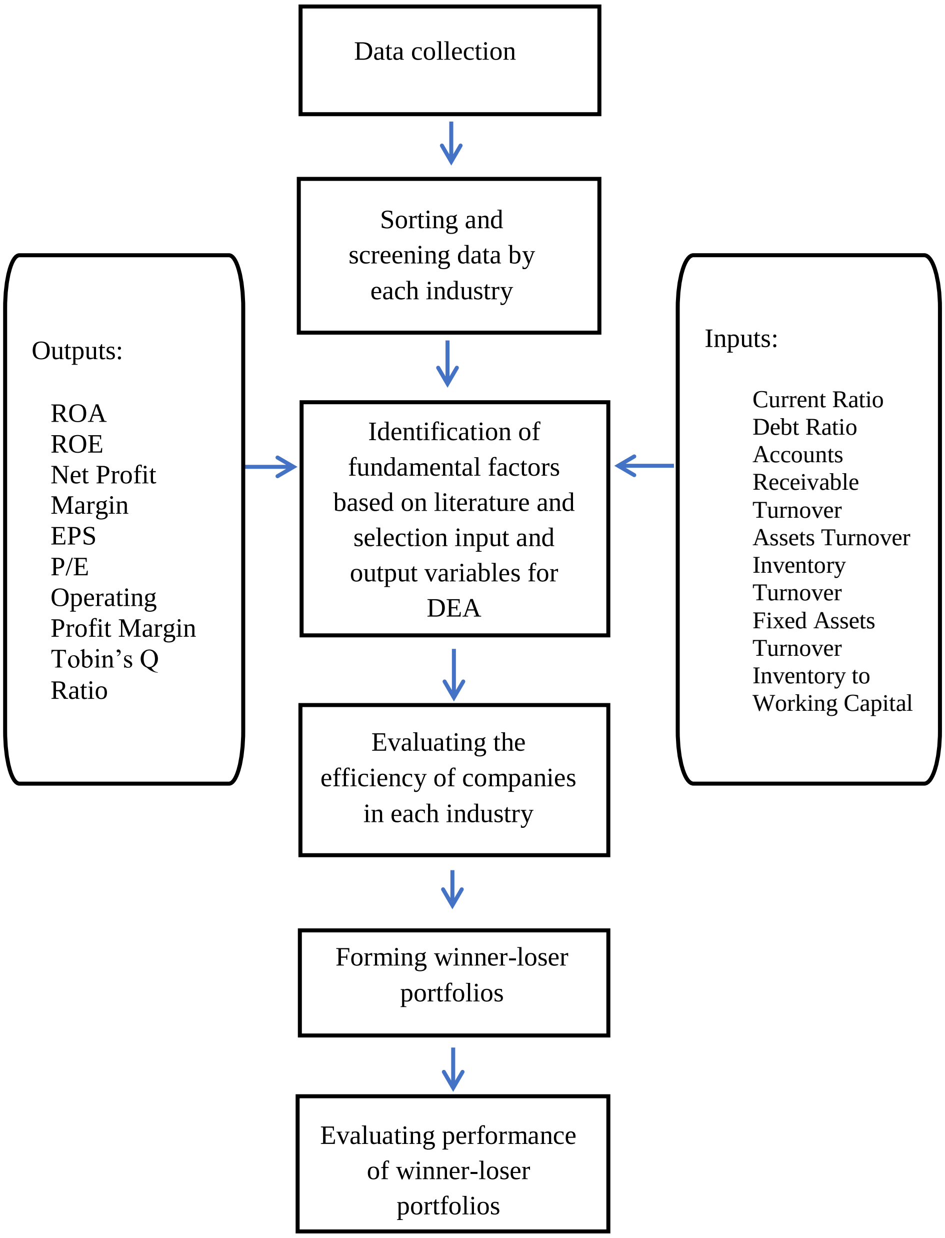


Table 5: List of Tested and Excluded Industries

Excluded industries		Tested industries
Industrial contracting Housing Engineering activity, analysis, and technical experiments Extraction of other mines Furniture Insurance and pension Paper products Auxiliary activities of intermediary financial institutions Leather products Extraction of oil and gas Engineering Wood products Electronic and optical computer products Other financial intermediaries Multidisciplinary industrial	Other transport Artistic, entertainment, and creative activities Coal mining Communication equipment Financial and monetary intermediation Wholesale and retail trade of motor vehicles Hotel and restaurant Telecommunications Printing Investments Medical tools Water transport Banks and credit institutions Retail Wholesale Information and communication Cultural and sports activities Textiles	Petroleum products Ceramics and tiles, Transportation, warehousing, and communication Food except sugar Sugar Supply of energy Extraction of metal ores Cement, lime, and plaster Rubber and plastic Basic metals Metal products Non-metallic mineral Machinery and equipment Cars and spare parts Computer Agriculture and related services Chemical Electrical devices Medicinal
During data screening, companies in the remaining industries whose information was incomplete were removed. Furthermore, the companies that were among the filtered industries, but whose field of activity was investment, were also removed. Moreover, the companies that passed the previous two filters, but had losses during the period under review, have also been removed		

3.3. Performance comparison test of winner-loser portfolios

To rigorously compare the performance of the winner and loser portfolios beyond simple mean comparisons, this study employs the concept of Stochastic Dominance (SD). SD is a non-parametric approach that does not require assuming a specific form for investor utility, making it a powerful tool for ranking investment strategies under uncertainty. It allows for a partial ordering of prospects (in this case, portfolio returns) that is consistent with the preferences of a broad class of utility-maximizing investors. We utilize first-, second-, and third-order stochastic dominance (FSD, SSD, TSD) tests to determine whether the returns of the winner portfolio consistently outperform those of the loser portfolio for investors with increasing, risk-averse, and skewness-loving utility functions, respectively.

The use of stochastic dominance over parametric tests: "Stochastic dominance is preferred here as it makes minimal assumptions about the underlying distribution of returns and the utility function of investors, relying only on general principles of non-satiation and risk aversion."

To mitigate the impact of potential outliers and data noise on our Data Envelopment Analysis results, we performed winsorization at the 1st and 99th percentiles for all input and output variables before running the DEA models. This process replaces extreme values with the nearest non-extreme values, effectively reducing their disproportionate influence on the efficiency frontier estimation while preserving the overall sample size and distributional characteristics. Given that DEA is a non-parametric frontier method that can be sensitive to extreme observations, this winsorization approach helps ensure that the efficiency scores reflect underlying operational performance rather than being distorted by anomalous data points resulting from reporting errors or one-off extraordinary events. The 2011–2023 period examined in this study encompasses significant economic volatility, including international sanctions, currency fluctuations, and macroeconomic instability characteristic of the Iranian market context. While winsorization helps mitigate the statistical influence of extreme values, we acknowledge that some degree of market volatility is inherent to the "real-world" environment in which investors make decisions. Therefore, our conclusions are framed within the context of this volatile period, recognizing that the efficiency-return relationships we document reflect actual market conditions faced by investors in the Tehran Stock Exchange rather than a controlled experimental setting. This explanation has been added to the methodology section to provide greater transparency regarding our data preparation procedures and their implications for interpreting the results.

The core of the testing procedure involves comparing the cumulative distribution functions (CDFs) of the returns from the winner portfolio ($F_W(r)$) and the loser portfolio ($F_L(r)$), where r represents the portfolio return. Let R_W and R_L be the random variables representing the returns of the winner and loser portfolios, with their respective CDFs, F_W and F_L (Davidson AND Duclos, 2000).

First-Order Stochastic Dominance (FSD): FSD is the most intuitive and strongest form of dominance. For all rational investors who prefer more wealth to less (i.e., have non-satiated utility functions, $U'(x) \ge 0$), portfolio W is said to first-order stochastically dominate portfolio L if its cumulative distribution function is always less than or equal to that of L, and strictly less for at least some return level.

Suppose that X and Y are random variables of two risky assets, with cumulative distribution functions F, $G,$ respectively, and U is a function of the investor's desirability. Moreover, all investors are insatiable (i.e., if $U'(x) \geq 0$ then $F(x) \leq G(x)\ \forall x$). Then, for all risk-averse investors, the asset with distribution function F is superior to the asset with distribution function G (Fong et al., 2008).

The formal condition is:
$F_W(\mathrm{r}) \leq F_L(\mathrm{r})$

for all possible returns r, with strict inequality for at least one value of r.

This condition leads to a simple visual rule according to which the CDF of the dominating portfolio lies below and to the right of the CDF of the dominated portfolio. This is because a lower CDF value at any given return r implies a higher probability of achieving a return greater than r. For instance, if at a 10% return, $F_W(0.10) = 0.3$ and $F_L(0.10) = 0.5$, it means the winner portfolio has a 70% chance of exceeding a 10% return, while the loser portfolio only has a 50% chance. We conduct this visual test by plotting the empirical CDFs of the six-month, one-year, and adjusted returns for both portfolios.

Second-Order Stochastic Dominance (SSD): Hadar and Russell (1969) introduced second-order stochastic dominance relationships in the field of economics and finance. Second-order stochastic dominance is based on two general assumptions of insatiability and risk aversion (for all investors), which leads to the assumption of downward concavity of the utility function at all points. Suppose that X and Y are random variables of two risky assets, with cumulative distribution functions F_A, $F_{B,}$ respectively, in the $[a, b]$ interval. For all risk-averse investors with the optimality function U, for all $U'(x) \geq 0$ and $U''(x) \leq 0$, if the following relationship holds, it can be concluded that said that F_A has second-order stochastic dominance over F_B (Fong et al., 2008). This is mathematically expressed as:

$$\int_{-\infty}^{x} [\, F_L(t) - F_W(t)]dt \geq 0\,, \forall x\ ;\ F_W = \int_{-\infty}^{x} F_W(t)dt\ , F_L = \int_{-\infty}^{x} F_L(t)dt$$

If FSD does not hold, or to test for dominance among a more specific class of investors, we turn to higher-order dominance tests. SSD applies to the set of all risk-averse and non-satiated investors (i.e., those with increasing and concave utility functions, where $U'(x) \ge 0$ and $U"(x) \le 0$). For these investors, portfolio W dominates portfolio L in the second order if the area under the CDF of W is always less than or equal to the area under the CDF of L up to any point.

Third-Order Stochastic Dominance (TSD): Third-order stochastic dominance adds the supremacy assumption, along with the skewness of the return distribution, to the risk-taking model. Suppose that F_A and F_B are the cumulative probability distributions of returns for two investments in the interval $[a, b]$. For all risk-averse investors with the optimal function U when $U(x) \geq 0$, $U''(x) \geq 0$, and $U'''(x) \geq 0$ and also if the expected return F_A is greater than the expected return F_B (i.e., $\mu_A > \mu_B$) and the following relation holds than it can be concluded that F_A has a third-order stochastic dominance over F_B (Fong et al., 2008).

$$\int_{-\infty}^{y} \int_{-\infty}^{x} [\, F_L(u) - F_W(u)]\, dudu \geq 0, \forall x, y$$

It worthy mentioned that the period studied includes significant macroeconomic shocks. State clearly that these factors are not directly modeled in the DEA. This is a major limitation. However, the use of industry-adjusted returns in evaluation partially controls for this. The logic is that all firms in an industry face similar macro conditions, so comparing a firm's return to its industry average helps isolate firm-specific performance from the macro tide.

4. Research Findings

4.1. Empirical Results

The efficiency scores of the winning portfolio (the top decile of high-performance companies) and the losing portfolio (the bottom decile of low-performance companies) are presented in Tables 6 and 7, respectively. Efficiency 2 to 5 is based on all input variables and one output variable. And efficiency column 1 is based on all input and output variables.

Table 6: Efficiency Scores of the Winning Portfolio from the Top Decile

Firm	**2011**					Firm	**2017**				
	Efficiency 1	Efficiency2 (output ROA)	Efficiency3 (output EPS)	Efficiency4 (output P/E)	Efficiency5 (output Tobin's Q)		Efficiency 1	Efficiency2 (output ROA)	Efficiency3 (output EPS)	Efficiency4 (output P/E)	Efficiency5 (output Tobin's Q)
Renovation and construction of Tehran	1	1	1	1	1	Tidewater Middle East	1	1	1	1	1
Sepahan Oil	1	1	1	1	1	Detergent industry management T.S. Behshahr	1	1	1	1	1
Kashi Hafez	1	1	1	1	1	Fars and Khuzestan cement	1	1	0.8183	1	0.9558
Pars Saram	1	1	1	1	1	Fajr Energy of the Persian Gulf	1	1	0.0001	1	0.9435
Charkheshgar	1	1	1	1	1	auto parts	1	1	1	1	1
Mehvarsazan	1	1	1	1	1	Mehrkam Pars	1	1	1	1	1
Megsal	1	1	1	1	0.9192	Asan pardakht persian	1	1	1	0.3894	1
	2012						2018				
Kashi pars	1	1	1	1	1	Iranian shipping	1	1	1	1	1
Iranian shipping	1	1	1	1	1	Tidewater Middle East	1	1	1	1	1
Mapna group	1	1	1	1	0.8388	Chadormeloo	1	1	1	1	1
Manganese mines of Iran	1	1	1	0.9057	0.5311	Opal mineral processing of Pars	1	1	1	1	1
Charkheshgar	1	1	1	1	0.7674	Detergent industry management T.S. Behshahr	1	1	1	0.5577	1
Sazeh pooyesh	1	1	1	0.2139	0.6318	Damavand mineral	1	1	1	1	1
Auto parts	1	1	1	1	0.3747	Behpardakhte melat	1	1	1	0.6803	0.8183
	2013						2019				
Isfahan sugar	1	1	1	0.1497	0.7437	auto parts	1	1	1	1	1
Lorestan sugar	1	1	1	0.2404	0.662	Tidewater Middle East	1	1	1	1	1

Sabanur mineral and industrial development	1	1	1	0.3354	0.6791	Sepahan Oil	1	1	0.8067	0.4783	0.7957
Sepenta	1	1	1	1	1	Lente Tormoz	1	1	0.3744	0.001	1
Informatics services	1	1	1	1	1	Asan pardakht persian	1	1	0.5418	0.2846	1
Hamkaran System	1	1	1	1	0.7026	FarsNo cement	1	1	0.8997	0.1682	0.7328
Megsal	1	1	1	0.9364	0.9618	Chodansazan	1	1	0.7947	0.2589	0.6594
	2014						2020				
Tehran oil refining	1	1	1	1	1	Renovation and construction of Tehran	1	1	1	1	1
Iranian shipping	1	1	1	1	1	Pars oil	1	1	1	1	1
Khorasan stable sugar	1	1	1	1	1	Opal mineral processing of Pars	1	1	1	1	1
Hormozgan cement	1	1	1	0.4632	0.6933	Sazeh pooyesh	1	1	1	1	1
Sahand rubber	1	1	1	0.9883	0.4134	Alumina of Iran	1	1	1	1	1
Jaam daroo	1	1	1	0.5446	0.8477	Damavand mineral	1	1	1	0.0068	1
Pars refractory product	1	1	1	1	1	Bama	1	1	1	0.3815	0.9867
	2015						2021				
Toka transportation	1	1	1	1	1	Zoobahan esfahan	1	1	1	1	1
Chadormeloo	1	1	1	1	1	Persian e-commerce	1	1	1	1	1
Dashestan cement	1	1	1	1	1	Detergent industry management T.S. Behshahr	1	1	1	0.865	1
Sepenta	1	1	1	1	1	Irka part sanat	1	1	1	1	0.3296
Pars refractory product	1	1	1	1	1	Kashi Pars	1	1	1	0.2475	0.8772
Bahman Group	1	1	1	1	0.9485	Bafagh Mines	1	1	1	0.7582	1
Megsal	1	1	1	1	0.8999	Behbahan Cement	1	1	1	0.2678	0.8944
	2016						2022				
Kashi Hafez	1	1	1	1	1	Alborz cable	1	1	1	1	1
Sepenta	1	1	1	1	1	Mapna group	1	1	1	0.9939	1
Asan pardakht persian	1	1	1	0.6075	1	Iranian shipping	1	1	1	1	0.3166
Fars and Khuzestan cement	1	1	0.9792	1	0.5873	Khash cement	1	1	1	0.2007	0.9116
Pharmaceutical factories	1	1	1	1	1	Lamiran	1	1	1	0.3332	0.741
Fajr Energy of the Persian Gulf	1	1	0.0003	1	1	Data processing of Iran	1	1	1	0.3812	0.9756
Pars oil	1	1	0.1993	1	0.8097	Kashi Sina	1	1	1	0.1825	0.6176

Table 7: Efficiency Scores of the Losing Portfolio from the Bottom Decile

Firm	2011					Firm	2017				
	Efficiency 1	Efficiency 2 (output ROA)	Efficiency 3 (output EPS)	Efficiency 4 (output P/E)	Efficiency 5 (output Tobin's Q)		Efficiency 1	Efficiency 2 (output ROA)	Efficiency 3 (output EPS)	Efficiency 4 (output P/E)	Efficiency 5 (output Tobin's Q)
Bandar Abbas oil refinery	0.1383	0.0661	0.0011	0.0053	0.1234	Zar makaron	0.1489	0.0016	0.0039	0	0.0038
Kavir tire	0.195	0.1457	0.0649	0.0003	0.0644	Korash food industry	0.2904	0.0852	0.0395	0	0.0178
Zoobahan esfahan	0.3946	0.071	0.0071	0.0134	0.387	Foolad sepid farabkavir	0.096	0.0708	0.0005	0.0002	0.0008
Electronic payment of Saman Kish	0.4629	0.1456	0.0485	0.018	0.0993	National lead and zinc	0.3035	0.0416	0.0009	0.003	0.3013
Petrochemical of nouri	0.2755	0.1474	0.0007	0.0002	0.001	simorgh	0.1859	0.1859	0.0548	0.0069	0.0189
Polypropylene jam	0.3128	0.1647	0.001	0.0004	0.0028	Arian Kimia Tech	0.2784	0.0009	0.0006	0.0004	0.0381
Persian Gulf Petrochemical Supplement	0.0728	0.0001	0.0003	0.0004	0.0145	Ghadir Petrochemical	0.149	0.1435	0.0004	0	0.022
	2012						2018				
Shahd of Iran	0.396	0.0101	0.0009	0.0076	0.3959	Zarnam Educators Industrial Research Group	0.1331	0.0018	0.0007	0	0.1331
Mobin energy of the Persian Gulf	0.4348	0.1693	0	0.033	0.195	Zar makaron	0.1716	0.0172	0.0021	0	0.0532
Kavir tire	0.3437	0.2279	0.0981	0.0004	0.0584	Foolad sepid farabkavir	0.3065	0.2798	0.0006	0.0001	0.0046
Electronic payment of Saman Kish	0.4086	0.2862	0.098	0.0194	0.0978	Ghaltaksazan sepahan	0.2571	0.0033	0.0011	0.0001	0.0005
Agriculture and animal husbandry of Pars	0.1559	0.1559	0.0212	0.0059	0.0138	Electronic payment of Pasargad Bank	0.1185	0.03	0.0071	0.0116	0.0723
Petrochemical of nouri	0.2879	0.1732	0.001	0	0.0016	Arian Kimia Tech	0.2476	0.0012	0.0001	0.0002	0.0322
Zangan distribution transformer	0.3498	0.0803	0.0459	0	0.0305	Zangan distribution transformer	0.2954	0.0491	0.0559	0	0.0363
	2013						2019				

Shahd of Iran	0.4486	0.154	0.0129	0.004	0.0001	Zarnam Educators Industrial Research Group	0.0591	0.0034	0.0013	0	0.0587
Plascokar Saipa	0.465	0.0042	0.002	0.0011	0.3262	Zar macarons	0.1704	0.0353	0.0067	0.0002	0.0014
Zoobahan esfahan	0.3836	0.0002	0.0026	0.003	0.2974	Alumina of Iran	0.3072	0.2701	0.2455	0.0037	0.0133
South Kish Kaveh steel	0.127	0.0568	0	0.0003	0.0837	Nord Aluminum	0.3192	0.2139	0.0061	0.0003	0.282
Alchemy of Zanjan Gostaran	0.4247	0.3997	0.0005	0.0001	0.0007	Electronic payment of Pasargad Bank	0.182	0.1251	0.0554	0.0181	0.1242
Petrochemical of nouri	0.3887	0.2965	0.0038	0.0001	0.0062	Arian Kimia Tech	0.3281	0.0935	0.0014	0.0003	0.0313
Zangan distribution transformer	0.348	0.1096	0.0528	0	0.028	Bo Ali Sina Petrochemical	0.2077	0.1877	0.0046	0.0003	0.0243
	2014						2020				
Petrochemical transportation engineering	0.5738	0.1025	0.0143	0.0813	0.5594	Korash food industry	0.5462	0.2044	0.0512	0	0.0007
South Kish Kaveh steel	0.3018	0.2499	0.0002	0.005	0.0693	Zoobahan esfahan	0.4545	0.2317	0.0068	0.0598	0.366
Zamiad	0.5876	0.0906	0.0273	0.0224	0.5876	Nord Aluminum	0.4912	0.3745	0.0119	0.0002	0.3918
Lente Tormoz	0.5904	0.0002	0.006	0.0035	0.5128	Kimia Zanjan Gostaran	0.5737	0.5737	0.0044	0.0001	0.0004
Mehvar Khodro	0.589	0.001	0.0069	0.0005	0.5701	Atmospheric factories	0.1455	0.0832	0.0097	0	0.0757
Ghadir Petrochemical	0.175	0.0009	0.0004	0	0.0005	auto parts	0.4059	0.2924	0.0607	0.0679	0.2962
Bo Ali Sina Petrochemical	0.3929	0.2233	0.0286	0.0004	0.0313	Electronic payment of Pasargad Bank	0.2141	0.1831	0.0961	0.0108	0.076
	2015						2021				
Zar macarons	0.2762	0.027	0.0078	0	0.0609	Behsaz Kashaneh Tehran	0.5027	0.301	0.0685	0.0861	0.498
South Kish Kaveh steel	0.2612	0.1624	0.0002	0.001	0.0908	Shaker Shahroud	0.5368	0.0064	0.0064	0.0308	0.5332
Alomorad	0.3021	0.0697	0.0021	0.0004	0.3019	Pipe and machine building	0.545	0.017	0.0011	0.0009	0.4787
National lead and zinc	0.1889	0.0007	0.0026	0.0002	0.0025	Electronic payment of Pasargad Bank	0.3963	0.3516	0.1096	0.0102	0.0676
Chodansazan	0.2156	0.1493	0.1843	0.0009	0.0437	Laabiran	0.4248	0.0104	0.0007	0.0002	0.4248
Ghadir Petrochemical	0.0891	0.0815	0.0003	0.0001	0.0002	Paksan	0.4877	0.1616	0.1482	0.0007	0.4318
Zangan distribution transformer	0.3139	0.0731	0.0595	0	0.0288	Fars chemical	0.4305	0.1694	0.0072	0.0227	0.234
	2016						2022				
Zar macarons	0.2697	0.0131	0.0029	0	0.0467	Georgian biscuits	0.4062	0.0483	0.0032	0.008	0.3524
Korash food industry	0.236	0.0292	0.012	0	0.0207	Bama	0.4586	0.3315	0.1558	0.2763	0.3352
Sabanur mineral and industrial development	0.271	0.0135	0.0011	0.0012	0.271	Pipe and machine building	0.3994	0.016	0.0002	0.0058	0.3614
South Kish Kaveh steel	0.2767	0.0452	0.0002	0.0002	0.1039	Mehvar khodro	0.4887	0.0932	0.0114	0.0082	0.4876
Foolad sepid farabkavir	0.1662	0.1146	0.0003	0.0002	0.0469	Pakshu Industrial Group	0.4393	0.328	0.008	0.0004	0.3423
Chodansazan	0.1664	0.1577	0.1184	0.0006	0.0184	Sinai Chemical	0.4439	0.3424	0.0224	0.0015	0.0064
Zangan distribution transformer	0.2045	0.0352	0.0335	0	0.0275	Fars chemical	0.2714	0.0047	0.0063	0.0014	0.0074

4.2. Descriptive statistics and comparison of win-loss portfolios

Descriptive statistics of returns and adjusted returns of future periods of loser-winner stocks are presented in Table 8. The return of the winning portfolio based on fundamental performance is significantly higher than the performance of the losing portfolios, except for the six-month future adjusted return. Moreover, descriptive statistics represent the high dispersion of returns in each portfolio. The higher negative skewness of the six-month returns of the winning portfolios compared to the losing portfolios indicates the presence of negative return sequences, which is more evident in the case of the winning portfolios. Although the difference in the six-month return of the winning portfolios compared to the losing portfolios is significant and significant, there are higher negative returns from winning portfolios than from losing portfolios.

Regarding the adjusted return of the next six months based on industry performance, the loser portfolio has a better performance than the winner portfolio, which can be due to the superiority of the intra-industry stock portfolio with lower fundamental efficiency than the efficient portfolio.

In terms of one-year forward performance, we see winners outperforming losers. However, they have underperformed over the six months, indicating that the momentum of winners relative to losers has decreased over longer periods. In terms of future adjusted returns, the performance of the winning portfolio is significantly superior to the losing portfolio. Based on descriptive statistics and comparing the performance of winning-losing portfolios, if there is a borrowing sale, taking buying positions on efficient stocks (winners) and selling positions on ineffective stocks (losers) can generate significant returns in future periods at least. Bring one year.

A notable finding requiring deeper examination is the underperformance of the winning portfolio relative to the losing portfolio in the six-month adjusted returns category. As reported in Table 8, the mean adjusted six-month return for the loser portfolio is positive (0.044), while the winner portfolio exhibits a negative mean adjusted return (-0.378), a statistically significant difference ($p < 0.01$). This result contradicts the main hypothesis that portfolios formed on fundamental efficiency should demonstrate superior future performance across all measurement horizons. Several complementary explanations may account for this anomalous finding.

Mean Reversion Effects: The first potential explanation involves short-term mean reversion in stock prices following periods of exceptional fundamental performance. Firms identified as "winners" based on DEA efficiency scores have achieved superior combinations of input minimization and output maximization, suggesting they are operating near their production possibility frontiers. Such high efficiency levels may be difficult to sustain in subsequent periods, particularly in the volatile economic environment characterizing the Tehran Stock Exchange. When benchmarked against industry performance (adjusted returns), these highly efficient firms may experience temporary price corrections as the market reassesses whether their exceptional efficiency is sustainable. This interpretation aligns with the behavioral finance literature on overreaction and correction (De Bondt and Thaler, 1985), where extreme performers subsequently experience reversals. The fact that this underperformance is observed only in the six-month horizon—and not in the one-year horizon—supports the mean reversion explanation, as short-term corrections may be followed by renewed recognition of fundamental strength over longer periods.

Industry Dynamics and Sectoral Shocks: A second explanation concerns the industry composition of winner and loser portfolios and differential exposure to sector-specific shocks. The loser portfolio, comprising firms with low DEA efficiency scores, may be concentrated in industries that experienced temporary positive shocks during specific six-month windows within our 2011–2023 sample period. These could include industries benefiting from favorable regulatory changes, temporary protection from imports, commodity price increases, or government contracts. When industry-adjusted returns are calculated by subtracting the weighted average industry return from individual stock returns, efficient firms operating in otherwise weak industries may appear to underperform relative to inefficient firms operating in temporarily strong industries. This interpretation suggests that industry effects can temporarily outweigh firm-specific fundamental efficiency in determining relative returns, consistent with the literature on industry momentum and the importance of sector allocation in portfolio performance.

Investor Attention and Turnaround Expectations: A third explanation involves shifts in investor attention and expectations. In emerging markets like Iran, where information asymmetry is pronounced and retail investors dominate trading activity, attention may flow disproportionately to firms with perceived "turnaround potential" rather than those already operating efficiently. Inefficient firms (losers) may attract speculative interest from investors anticipating operational improvements, restructuring, or favorable resolution of financial difficulties. This attention can create short-term price pressure that temporarily elevates the returns of inefficient firms relative to their industries. Meanwhile, efficient firms may be perceived as "steady but unexciting" investments, attracting less speculative attention and consequently exhibiting more modest short-term returns. This explanation draws on the literature regarding investor sentiment and limited attention (Barber and Odean, 2008), suggesting that the six-month horizon captures periods when inefficient firms become the focus of speculative interest before fundamentals ultimately prevail over longer horizons.

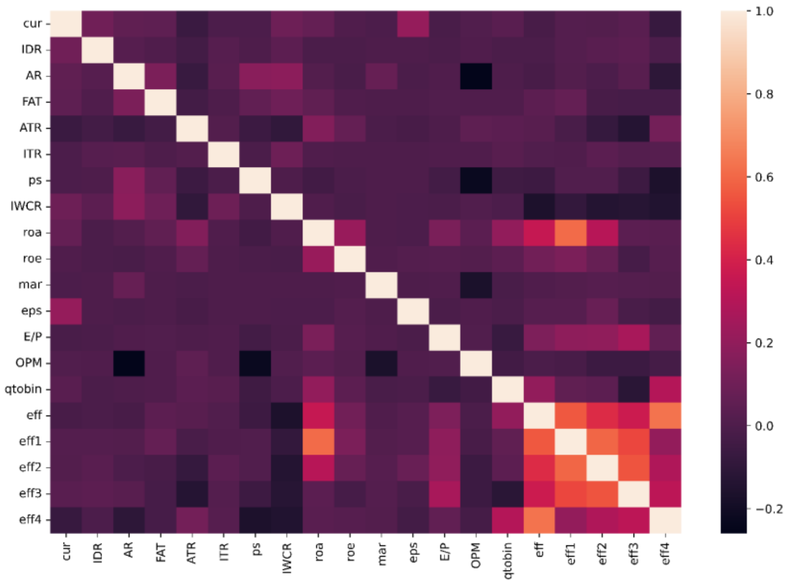
Interaction of Multiple Factors: Most plausibly, these explanations are not mutually exclusive but interact to produce the observed pattern. The six-month adjusted return underperformance of winner portfolios likely reflects a combination of: (1) temporary price corrections following periods of exceptional efficiency, (2) differential industry exposures that temporarily favor inefficient-firm industries, and (3) speculative attention directed toward turnaround candidates. The subsequent reversal to superiority over the one-year horizon suggests that these short-term effects dissipate as fundamental efficiency reasserts its influence on returns. This interpretation adds important nuance to our findings: while fundamental efficiency ultimately predicts superior long-term performance, investors should anticipate potential short-term underperformance of efficient stocks on an industry-adjusted basis. For portfolio managers implementing winner-loser strategies based on DEA efficiency, this implies that six-month underperformance should not necessarily trigger strategy abandonment, as the relationship reverses over longer holding periods consistent with the momentum literature.

Finally, according to the descriptive statistics and the existence of trailing returns that have led to positive and negative deviations of the returns of winning-losing stocks, the stochastic dominance test is used to compare the effectiveness of investment strategies based on fundamental efficiency analysis.

Table 8: Returns and Adjusted Returns of Loser-Winner Stocks

Return type	Loser portfolio				Winner portfolio				Difference	Sig.
	Mean	Standard Deviation	Skewness	Kurtosis	Mean	Standard Deviation	Skewness	Kurtosis		
The next six months	-1.33	0.254	-0.537	1.414	2.357	0.761	-1.271	0.317	2.490	0.00
Adjusted the next six months	0.044	0.173	1.539	1.929	-0.378	0.767	-1.278	0.311	-0.423	0.00
Next one year	0.032	0.118	-3.349	9.254	1.154	2.013	1.925	1.731	1.112	0.00
Adjusted one year	-0.033	0.118	-3.349	9.255	0.775	2.013	1.925	1.731	0.807	0.00

Figure 2: Heat Map Diagram of The Correlation Matrix of Input-Output Variables of the DEA Model

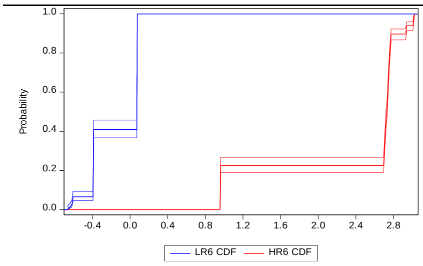


In order to check the accuracy and increase the confidence factor of the results obtained from the efficiency scores, we performed a sensitivity analysis on the efficiency scores based on the single outputs of the output variables of the model. The heat map diagram of the correlation matrix confirms the accuracy of the results obtained from the efficiency scores (Figure 2). As the figure indicates, the 5 calculated efficiency scores have an acceptable correlation with each other. Also, considering the relatively high correlation between ROA and the three efficiency scores calculated (Efficiency 1, Efficiency 2, and Efficiency 3), it can be concluded that ROA has a great positive effect on the efficiency scores obtained from these three approaches.

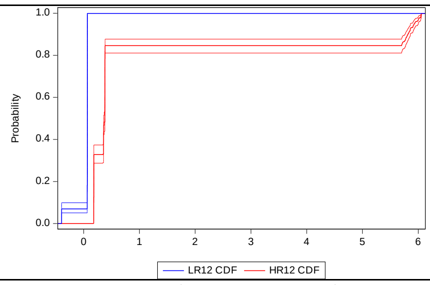
4,3. The Results of the Stochastic Dominance

Before performing the stochastic dominance statistical test, the first-order visual stochastic dominance test is performed based on the comparison of the cumulative distribution level of the performance of efficient-inefficient portfolios, assuming investors' risk aversion. If the cumulative return distribution level of a portfolio is below and to the right of another portfolio, it indicates first-order stochastic dominance. Therefore, as seen in Figure 3 (a, b, and d), the return of the efficient portfolio has a first-order stochastic dominance over the return of the ineffective portfolio, assuming investors' risk aversion.

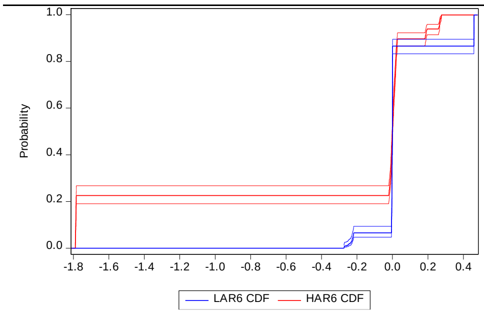
Figure 3: First-Order Stochastic Dominance Test of Two Winning And Losing Portfolios



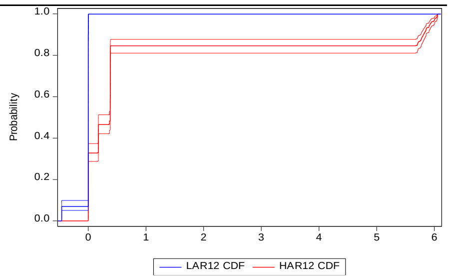
a: Comparison of distribution of six-month cumulative return of effective-inefficient portfolios



b: Comparison of distribution of one-year cumulative return of effective-inefficient portfolios



c: Comparison of six-month cumulative adjusted return distribution of effective-inefficient portfolios



d: Comparison of one-year cumulative adjusted return distribution of effective-inefficient portfolios

Table 9 represents the results of the second- and third-order stochastic dominance statistical test comparing the returns of efficient and non-efficient stock portfolios for six-month and one-year periods after the portfolio was formed. As the table demonstrates, the six-month returns of efficient and non-efficient portfolios are above the critical value of 3.25. This result indicates the six-month future returns of the efficient portfolio dominate the six-month future returns of the non-efficient portfolio in both the second and third orders. This stochastic dominance of the six-month future return of the efficient portfolio over the non-efficient portfolio is observed in all decimations, so that according to Figure 3 (section a), the distribution trend line of the cumulative six-month future return of the efficient portfolio (red line) is placed under the trend line of the future distribution of the cumulative six-month return of the inefficient portfolio (blue line). This situation is established in all tithes of six-month future returns of both effective and ineffective portfolios. This means that the six-month future return of the efficient portfolio has a first-order stochastic dominance over the six-month future return of the ineffective portfolio, assuming the risk aversion of investors, and the numerical results of Table 9 are confirmed by the test statistics of levels 2 and 3.

Similarly, according to the results of the second and third-order stochastic dominance test of the six-month adjusted future return of the efficient portfolio against the non-efficient portfolio, the values obtained from the decimalization of the future return are smaller than the critical value of 3.25. That indicates the stochastic dominance of the second and third orders of the six-month adjusted future return of the ineffective portfolio over the six-month adjusted future return of the efficient portfolio. In addition, this stochastic dominance of the six-month adjusted future return of the inefficient portfolio over the efficient portfolio is observed in all decimations, so that according to Figure 3 of the part c, the distribution trend line of the six-month adjusted future returns cumulative efficient portfolio (red line) is above the trend line of the distribution trend of six-month adjusted future return of ineffective portfolio (blue line) in all decimations. This means that the six-month adjusted future return of the effective portfolio has a first-order stochastic dominance over the six-month adjusted future return of the ineffective portfolio, assuming investors' risk aversion, and confirming the numerical results of Table 9 of the test statistic.

Table 9: Second and Third Stochastic Dominance Test

Tithes	Six-months test		Adjusted Six-months test		One-year test		Adjusted One-year test	
	Second order	Third order	Second order	Third order	Second order	Third order	Second order	Third order
0.1	7.141	12.574	6.027	10.555	-10.017	-9.683	12.804	14.347
0.2	9.680	14.969	9.278	17.022	-9.993	-9.708	13.726	16.881
0.3	11.727	15.608	12.470	18.089	-9.983	-9.867	14.858	18.315
0.4	13.115	15.775	14.620	18.220	-9.996	-10.132	15.918	19.170
0.5	13.864	15.483	15.695	17.763	-10.026	-10.281	16.821	19.708
0.6	14.235	15.162	16.188	17.274	-10.055	-10.281	17.560	20.066
0.7	14.417	14.833	16.405	16.785	-10.078	-10.281	18.155	20.313
0.8	14.492	14.511	16.471	16.314	-10.097	-10.281	18.633	20.491
0.9	14.501	14.202	16.448	15.870	-10.114	-10.281	19.017	20.622
1	14.467	13.911	16.370	15.458	-10.128	-10.281	19.330	20.740

Similar to the second and third order stochastic dominance test of the one-year future returns of the efficient portfolio over the non-efficient portfolio, the obtained values are higher than the critical value of 3.25, and this indicates the second and third order stochastic dominance of the one-year future returns of the efficient portfolio over the one-year future returns of the inefficient portfolio. Also, this stochastic dominance is observed in all decimals of one-year future return for efficient and non-efficient portfolios, so that according to Figure 3 of the second part, the distribution trend line of the cumulative one-year future return of the efficient portfolio (red line) is placed under the trend line of the distribution of one-year cumulative future returns of the inefficient portfolio (blue line), in all deciles.

In the second and third order stochastic dominance test of one-year adjusted future returns of efficient portfolio versus non-efficient portfolio, the obtained values are all higher than the critical value of 3.25, and this indicates the second and third order stochastic dominance of one-year adjusted future portfolio returns. This stochastic dominance is observed in all the deciles of one-year adjusted future returns for efficient and non-efficient portfolios, as shown in Figure 3, part d, the distribution trend line of cumulative one-year adjusted future returns the efficient portfolio (red line) is placed under the trend line of the adjusted one-year cumulative future return distribution of the inefficient portfolio (blue line). These conditions indicate that the one-year adjusted future return of the effective portfolio has a first-order stochastic dominance over the one-year adjusted future return of the inefficient portfolio, assuming the risk aversion of investors, and confirming the numerical results of Table 9.

5. Conclusion

In the analysis of stock portfolios, DEA serves as a powerful tool to identify companies with superior operational efficiency by analyzing the relationships between their internal inputs and outputs. This study applied an input-oriented DEA model to a sample of 382 companies on the Tehran Stock Exchange from 2011 to 2022. By evaluating intra-firm factors—including current ratio, debt ratio, and various turnover ratios as inputs, and profitability metrics like ROA, ROE, and Tobin's Q as outputs—we classified firms into efficient (winner) and inefficient (loser) portfolios within their respective industries.

The subsequent performance analysis of these portfolios yields critical and nuanced insights for investors. While a simple comparison of mean one-year future returns shows a clear superiority of winner stocks over losers, the analysis of six-month adjusted returns (which account for industry performance) tells a different story. In this shorter horizon, the loser portfolio outperformed the winner. This suggests that the market's pricing of fundamental efficiency is not instantaneous and that industry-wide momentum can temporarily overshadow firm-specific fundamentals. These findings lead to concrete, actionable investment guidance that moves beyond generic recommendations. The results suggest that a long-term investment strategy (one year or more) can be enhanced by constructing a portfolio of stocks with high DEA efficiency scores. Investors should focus on maintaining positions in these winners to capture their superior long-term returns. The one-year stochastic dominance of winner portfolios indicates that a "buy-and-hold" approach on high-efficiency stocks is likely to generate superior risk-adjusted returns. This strategy aligns with the view that the market eventually rewards firms with strong operational and financial fundamentals.

However, a different approach is warranted for shorter investment horizons. For investors with a shorter-term horizon (e.g., six months), the adjusted return performance of efficient stocks is weaker. A strategy based purely on efficiency may underperform the industry benchmark in the short run. Therefore, short-term traders should be cautious about relying solely on this signal and might consider combining it with technical indicators or momentum factors. Our finding of six-month adjusted return dominance by the loser portfolio suggests that short-term market dynamics can dominate firm-specific fundamentals, and a prudent short-term trader must look beyond static efficiency screens. Importantly, all investors must recognize that firm fundamentals and their associated efficiency scores are not static. In periods of rapid economic change, such as currency devaluation, investors should re-run the DEA analysis quarterly, as historical efficiency may become a less reliable predictor when the fundamental landscape is shifting. Pay close attention to how input variables like debt ratios and inventory turnover react to the new macro environment. This dynamic approach to portfolio management enables the timely identification of firms whose fundamentals are improving or deteriorating, facilitating proactive rebalancing to capture new winners and divest from declining losers.

Using the Tehran Stock Exchange as a case study for an emerging market facing unique economic conditions, this research provides valuable insights while acknowledging certain limitations. Determining fundamental efficiency based on internal factors represents a common methodological approach; however, numerous external factors influence company performance and stock returns. This study has not incorporated the effects of external factors—such as macroeconomic conditions, regulatory changes, or global market dynamics—that may significantly impact company performance and stock valuations. Future research should investigate the effects of external factors in evaluating winner-loser investment portfolios and compare these findings with the present study. An additional important consideration is that the financial indices employed in this research exhibit some dependence on previously documented results, potentially introducing bias that could affect the out-of-sample predictive ability of the strategy. Whether the market behavior documented in this study represents market inefficiency or results from rational pricing strategies remains an open question for future investigation. The single-market focus on the Tehran Stock Exchange, while providing detailed insights into an emerging market context, limits the generalizability of results to other emerging or developed markets with different regulatory frameworks, institutional structures, and economic conditions. Comparative studies across multiple markets would enhance understanding of how institutional and regulatory differences moderate the relationship between fundamental efficiency and subsequent stock returns. Moreover, this study ignored the effect of external factors that can affect the performance of companies and stock prices. Therefore, future studies may investigate the effects of external factors on the evaluation of win-loss investment portfolios and compare the results with those of the current research. This study does not isolate firm-level efficiency from macro effects, and this is a key area for future research. "Future research could integrate macroeconomic variables (e.g., inflation rates, exchange rates, sanctions indices) directly into the DEA framework or use them as second-stage repressors to disentangle firm-level efficiency from the overwhelming impact of the economic environment.

Acknowledgements

Ethical approval: We confirm that all the research meets the ethical guidelines, including adherence to the legal requirements of the study country.

Funding: No funding is received by this study.

Conflict of Interest: The authors declare that they do not have any conflict of interest in other works

References

Abarbanell, J. S., & Bushee, B. J. (1997). Fundamental analysis, future earnings, and stock prices. Journal of accounting research, 35(1), 1-24.

Arasu, B. S., Kannaiah, D., Nancy Christina, J., & Shabbir, M. S. (2021). Selection of variables in data envelopment analysis for evaluation of stock performance. Management and Labour Studies, 46(3), 337-353.

Arsad, R., Abdullah, M. N., Alias, S., & Isa, Z. (2017). Selection input output by restriction using DEA models based on a fuzzy Delphi approach and expert information. In Journal of Physics: Conference Series (Vol. 892, No. 1, p. 012010). IOP Publishing.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies, 21(2), 785-818.

Bekaert, G., & Wang, X. (2010). Inflation risk and the inflation risk premium. *Economic Policy*, *25*(64), 755-806.

Beneish, M. D., Lee, C. M., & Tarpley, R. L. (2001). Contextual fundamental analysis through the prediction of extreme returns. Review of Accounting Studies, 6, 165-189.

Bodie, Z., Kane, A., & Marcus, A. J. (2021). Investments, 12th Edn. McGraw-Hill Education.

Breitung, C. (2023). Automated stock picking using random forests. Journal of Empirical Finance, 72, 532-556.

Caner, M., & Fan, Q. (2025). A Practitioner's Guide to AI+ ML in Portfolio Investing. Available at SSRN 5546200.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European journal of operational research, 2(6), 429-444.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). Data envelopment analysis: a comprehensive text with models, applications, references and DEA-solver software (Vol. 2, p. 489). New York: springer.

Davidson, R., & Duclos, J. Y. (2000). Statistical inference for stochastic dominance and for the measurement of poverty and inequality. Econometrica, 68(6), 1435–1464.

Ebrahimi, B., & Hajizadeh, E. (2021). A novel DEA model for solving performance measurement problems with flexible measures: An application to Tehran Stock Exchange. Measurement, 179, 109444.

Fong, W. M., Lean, H. H., & Wong, W. K. (2008). Stochastic dominance and behavior towards risk: The market for internet stocks. Journal of Economic Behavior & Organization, 68(1), 194-208.

Fontanills, G. A., & Gentile, T. (2002). The stock market course (Vol. 117). John Wiley & Sons.

Ghandehari, M., Azar, A., Yazdanian, A. R., & Golarzi, G. (2019). A Hybrid Model of Stochastic Dynamic Programming and Genetic Algorithm for Multistage Portfolio Optimization with GlueVaR Risk Measurement. *Industrial Management Journal*, *11*(3), 517-542.

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, 33(5), 2223–2273. https://doi.org/10.1093/rfs/hhaa009

Hadar, J., Russell, W.R., (1969). Rules for ordering uncertain prospects. American Economic Review 59, 25–34.

Hasanah, A., Istiqomah, S., Adam, A. M., Kharisma, B., & Remi, S. S. (2025). Single mother status and children education: Evidence from Indonesian panel data. Journal of Economic Cooperation and Development, 46(3), 1–24.

Hull, J. C. (2003). Options futures and other derivatives. Pearson Education India.

Jothimani, D., Shankar, R., & Yadav, S. S. (2017). A PCA-DEA framework for stock selection in Indian stock market. Journal of Modelling in Management, 12(3), 386-403.

Kara, K., & Çetinkaya, A. S. L. I. (2022). Determination of Financial Performance Efficiency with Data Envelopment Analysis: Evidence from Borsa İstanbul (BIST) Transportation and Storage Sector. Journal of emerging economies and policy (Online), 7(2).

Karimi, A., & Barati, M. (2018). Financial performance evaluation of companies listed on Tehran Stock Exchange: A negative data envelopment analysis approach. International Journal of Law and Management, 60(3), 885-900.

Külpmann, Mathias (2004) Irrational Exuberance Reconsidered:The Cross Section of Stock Returns, second edition, Springer Finance (FINANCE).

Kumbure, M. M., Tarkiainen, A., & Luukka, P. (2023). A hybrid machine learning approach for stock market forecasting and portfolio selection. Expert Systems with Applications, 234, 121058. https://doi.org/10.1016/j.eswa.2023.121058

Lev, B., Thiagarajan, R., 1993. Fundamental information analysis. J. Account. Res. 31, 190–214.

Lim, S., Oh, K. W., & Zhu, J. (2014). Use of DEA cross-efficiency evaluation in portfolio selection: An application to Korean stock market. European Journal of Operational Research, 236(1), 361–368.

Majeed, S., Iqbal, T., & Moin, N. (2025). Effects of banking sector credits in estimating import demand of Pakistan: Evidence from FMOLS and DOLS approach. Journal of Economic Cooperation and Development, 46(3), 25–48.

Markowitz, H. M. (1952). "Portfolio selection. Journal of finance". pp: 77- 91.

Mohanram, P. S. (2005). Separating winners from losers among lowbook-to-market stocks using financial statement analysis. *Review of accounting studies, 10*, 133-170.

Mohr, J. H. M. (2012). Utility of Piotroski F-score for predicting growth-stock returns. MFIE Capital, 30.

Ou, J. A., & Penman, S. H. (1989). Accounting measurement, price-earnings ratio, and the information content of security prices. Journal of accounting research, 27, 111-144.

Peykani, P., Seyed Esmaeili, F. S., Mirmozaffari, M., Jabbarzadeh, A., & Khamechian, M. (2022). Input/output variables selection in data envelopment analysis: A shannon entropy approach. Machine Learning and Knowledge Extraction, 4(3), 688-699.

Piotroski, J. D. (2000). Value investing: The use of historical financial statement information to separate winners from losers. Journal of Accounting Research, 1-41.

Qu, B. Y., & Suganthan, P. N. (2011). Constrained multi-objective optimization algorithm with an ensemble of constraint handling methods. *Engineering Optimization*, *43*(4), 403-416.

Roncalli, T. (2020). Handbook of financial risk management. CRC press.

Salimi, S., & Shahriari, M. (2023). Ranking and evaluation of financial efficiency of pharmaceutical companies accepted in Tehran Stock Exchange with the approach of data envelopment analysis and multi-criteria decision making. Advances in Mathematical Finance and Applications, 8(1), 219-240.

Senfi, S., Sheikh, R., & Sana, S. S. (2024). A portfolio selection using the intuitionistic fuzzy analytic hierarchy process: A case study of the Tehran Stock Exchange. *Green Finance*, *6*(2), 219-248.

Shabbir, M. S., & Muhammad, I. (2019). The dynamic impact of foreign portfolio investment on stock prices in Pakistan. Transnational Corporations Review, 11(2), 166–178.

Singh, S., & Yadav, S. S. (2021). *Security Analysis and Portfolio Management: A Primer*. Springer Nature.

Thomsett, M. C. (2006). Getting started in fundamental analysis. John Wiley & Sons.

Wang, X., Wang, B., Li, T., Li, H., & Watada, J. (2023). Multi-criteria fuzzy portfolio selection based on three-way decisions and cumulative prospect theory. *Applied Soft Computing*, *134*, 110033.

Zhou, Z., Gao, M., Xiao, H., Wang, R., & Liu, W. (2021). Big data and portfolio optimization: a novel approach integrating DEA with multiple data sources. *Omega*, *104*, 102479.