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RESEARCH PAPER

Construction and Back-Testing of an Indexed Portfolio by Using Constrained Regression with Transaction Costs, Weight Constraints, and Asset Turnover in the Iranian Capital Market

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Abstract
This paper considers 5 large stocks for retail investors and 14 stocks that cover almost the entire market for institutional investors to build an indexed portfolio. This research uses a constrained regression approach to build this portfolio for a 1-year and 2-year period, taking into account real-world constraints including transaction costs, asset turnover in the portfolio, and weight constraints. First, the companies under study are introduced, and then their performance over the entire period is examined. Second, the portfolio weights are updated in 21-day periods for one year and two years. Third, a t-test is run to statistically evaluate the performance of this portfolio with the overall index. The results show that in the two-year and one-year periods, these portfolios have statistically significantly outperformed the overall index. It seems that by balancing the portfolio weights in a periodic manner, one can achieve better performance than the overall index. Therefore, this approach can be suitable for retail and institutional investors.

Keywords: Constrained Regression, Indexed Portfolio Construction, Market Outperformance, Portfolio Rebalancing, Transaction Costs.
JEL Classification: C61, G11.

1. Introduction

In contemporary financial theory and practice, the construction and management of investment portfolios are central to optimizing the trade-off between risk and return. As financial markets become increasingly complex, investors—both institutional and individual—face the challenge of constructing portfolios that not only maximize returns but also align with their financial goals, risk tolerances, and investment horizons. Three interrelated pillars address this challenge: portfolio construction, portfolio optimization, and indexing. Each concept contributes uniquely to investment decision-making, yet they form a cohesive framework for achieving disciplined and evidence-based portfolio management.

Portfolio construction is the foundational step in investment management. It involves the selection and allocation of asset classes, sectors, and individual securities, guided by investor-specific constraints and objectives. The necessity of this stage lies in the pursuit of diversification, which reduces unsystematic (idiosyncratic) risk (Fabozzi et al., 2002). Strategic asset allocation frameworks often incorporate macroeconomic indicators, investor preferences, and regulatory limitations to establish a structured and resilient investment strategy.

The evolution of portfolio optimization began with the groundbreaking work of Harry Markowitz (1952), who introduced Modern Portfolio Theory (MPT). MPT formalized the notion of diversification by demonstrating that investors can construct an efficient frontier of portfolios that maximize expected return for a given level of risk. The model uses statistical measures—expected return, standard deviation, and asset correlations—to determine optimal asset weights.

This theoretical framework was extended by the Capital Asset Pricing Model (CAPM) (Sharpe, 1964; Lintner, 1965), which introduced beta as a measure of an asset's systematic risk relative to the market. CAPM provided a way to estimate expected returns based on market sensitivity and the risk-free rate, strengthening the analytical foundation of portfolio selection.

As empirical research began to question the consistent outperformance of active strategies, the concept of indexing—or passive portfolio management—emerged as a cost-efficient alternative. Indexing involves replicating the performance of a broad market index (e.g., S&P 500, MSCI World) using full or partial replication techniques. The rationale behind indexing is grounded in the Efficient Market Hypothesis (EMH), which argues that asset prices reflect all available information, making it difficult to consistently outperform the market (Fama and French, 1993).

Malkiel (2003) and Bogle (1999) championed this approach, emphasizing lower costs, tax efficiency, and simplicity. Longitudinal studies (Fama and French, 2010; SPIVA, 2023) consistently show that a large majority of actively managed funds underperform their benchmarks over long horizons.

Modern portfolio optimization has advanced well beyond the mean-variance framework. Key innovations include:

- Post-Modern Portfolio Theory (PMPT): Recognizes investor asymmetry in risk preferences and emphasizes downside risk over variance (Sortino and Price, 1994).

- Black-Litterman Model: Combines equilibrium returns with investor views in a Bayesian framework to produce more stable portfolios (Black and Litterman, 1992).
- Robust Optimization: Tackles parameter uncertainty by incorporating confidence intervals into optimization inputs (Fabozzi et al., 2007).
- Machine Learning Applications: Techniques like neural networks and reinforcement learning offer dynamic and adaptive approaches to asset allocation (Dixon et al., 2020).

Moreover, practical portfolio implementation must navigate real-world constraints, such as:

- Transaction costs (Lobo et al., 2007),
- Cardinality constraints (Jobst et al., 2001),
- Liquidity considerations (Almgren and Chriss, 2001).

Indexing has diversified beyond traditional market-cap weighted indices. New methodologies include:

- Fundamental Indexing: Weights stocks based on financial metrics (e.g., earnings, dividends) rather than market capitalization (Arnott et al., 2005).
- Equal-Weighting: Allocates equal capital to each constituent, enhancing diversification (Fernholz et al., 1998).
- Smart Beta: Applies factor-based tilts (e.g., value, momentum, low volatility) within an index-based framework (Ang, 2014; Arnott et al., 2013).

Recent developments blur the line between active and passive strategies:

- Smart Beta Strategies: Factor investing with passive implementation (Asness et al., 2013).
- Direct Indexing: Custom index replication with tax-loss harvesting and personalization (Sullivan, 2021).
- Risk-Targeted Index Funds: Combine passive indexing with volatility targeting (Chow et al., 2011).

Empirical data consistently supports the superior cost-efficiency and performance persistence of indexed strategies:

- Indexed funds typically have lower expense ratios compared to actively managed funds (Bogle, 1999).
- Over a 15+ year period, approximately 90% of active U.S. equity funds underperformed the S&P 500 benchmark (SPIVA, 2023).

Smart beta and hybrid indexing approaches offer the promise of improved risk-adjusted returns while maintaining the structural benefits of passive investing. This research extends the theoretical and empirical portfolio management literature to the Iranian capital market, an emerging market with high investment potential. The specific contributions of this study include:

- Development of an Indexed Portfolio: Tailored for both retail and institutional investors within Iran's capital market, considering local asset characteristics and market structure.
- Incorporation of Real-World Constraints: The model accounts for transaction costs, turnover limits, and weight constraints relevant to domestic trading conditions.
- Constrained Regression Model: An index-tracking model is built using constrained regression to approximate the Tehran Stock Exchange benchmark index using a limited subset of representative companies.
- Back-testing and Performance Evaluation: The constructed portfolio is evaluated using historical data to assess tracking error and relative performance.

The study provides practical implications for portfolio managers and policymakers in emerging markets by showcasing how index-based strategies can be adapted under localized constraints.

The remainder of the paper is organized as follows:

- Section 2 presents a detailed review of the relevant literature.
- Section 3 introduces the dataset and outlines the methodology, including the constrained regression model.
- Section 4 reports the empirical results and back-testing performance.
- Section 5 concludes the paper with key findings and policy recommendations.

2. Research Literature

This section reviews the academic and empirical literature across four key areas: (1) portfolio construction, (2) portfolio optimization, (3) indexing and passive management, and (4) new frontiers in investment theory and practice.

2.1 Literature on Portfolio Construction

2.1.1 Foundations of Diversification and Risk Management

The concept of diversification is one of the earliest principles in finance, formalized through Modern Portfolio Theory (MPT) by Markowitz (1952). MPT introduced the mean-variance framework, showing that combining assets with low correlations can reduce overall portfolio risk. The theory emphasized optimizing the trade-off between expected return and variance.

This framework was expanded by Sharpe (1964) with the Capital Asset Pricing Model (CAPM), which introduced beta as a systematic risk measure. Later, Ross (1976) developed the Arbitrage Pricing Theory (APT), and Fama and French (1993; 2015) introduced multi-factor models, showing that size, value, profitability, and investment factors explain cross-sectional asset returns more comprehensively than market beta alone.

2.1.2 Strategic and Behavioral Extensions

From a practical standpoint, Strategic Asset Allocation (SAA) and Tactical Asset Allocation (TAA) became key portfolio construction approaches, with SAA defining a long-term asset mix and TAA allowing short-term market-based adjustments (Illmanen, 2011).

However, MPT faced critiques for relying on unrealistic assumptions such as normal return distributions and static correlations, especially during financial crises. Mandelbrot (1963) and Taleb (2007) emphasized the need to consider fat tails and extreme events, arguing that traditional models underestimate tail risks. Rockafellar and Uryasev (2000) responded with Conditional Value-at-Risk (CVaR) as a more robust risk metric.

Behavioral finance scholars, notably Kahneman and Tversky (1979) and Thaler (1999), demonstrated that psychological biases distort investor decision-making. Shefrin and Statman (2000) proposed Behavioral Portfolio Theory, where investors create mental "layers" in portfolios based on goals rather than optimizing global utility.

2.1.3 Innovations in Asset Classes and Methods

Advances in portfolio construction also include the Black-Litterman model (1992), which combines market equilibrium with investor views to improve portfolio weights, and Risk Parity (Qian, 2005), which allocates capital by risk contribution rather than notional amounts.

The rise of alternative assets—including private equity, real estate, and commodities—was championed by Swensen (2000) and Gorton and Rouwenhorst (2006), who demonstrated diversification and inflation-hedging benefits. More recently, Brière et al. (2015) explored the inclusion of cryptocurrencies as diversifiers, despite their high volatility and unstable correlations.

2.2 Portfolio Optimization Literature

2.2.1 Classical Optimization and Critiques

Portfolio optimization builds directly on MPT. Yet its practical limitations—particularly estimation error—have been well documented. Michaud (1989) critiqued mean-variance optimization (MVO) for being overly sensitive to input assumptions. Best and Grauer (1991) showed that small variations in expected returns can yield dramatically different portfolio outcomes.

2.2.2 Bayesian and Resampling Enhancements

To improve robustness, researchers introduced Bayesian and resampling approaches. Jorion (1986) proposed Bayesian shrinkage estimators, which reduce noise by blending priors with sample statistics. Black and Litterman (1992) improved optimization by blending equilibrium market returns with subjective investor views.

Michaud and Michaud (2008) developed resampling methods that create multiple efficient frontiers through Monte Carlo simulation, leading to more stable and diversified portfolios. He and Litterman (2002) showed that these approaches reduce turnover by up to 70% while maintaining intuitive allocations.

2.2.3 Real-World Constraints and Multidimensional Objectives

Contemporary research integrates practical constraints:

- Liquidity-aware optimization models by Acharya and Pedersen (2005),
- Tax-aware frameworks by Apelfeld et al. (1996),
- and robust optimization by Fabozzi et al. (2007) to address parameter uncertainty.

A further evolution has been the inclusion of Environmental, Social, and Governance (ESG) considerations. Pedersen et al. (2021) developed the ESG-efficient frontier, allowing investors to assess trade-offs between financial returns and sustainability.

2.2.4 Machine Learning in Optimization

Recent work explores machine learning to overcome the limitations of linear models. Gu et al. (2020) applied deep learning to detect nonlinear patterns in alternative data, improving portfolio predictions. Reinforcement learning techniques (Dixon et al., 2020) are being used for dynamic allocation and rebalancing under uncertainty.

2.3 Literature on Indexing and Passive Portfolio Management

2.3.1 Theoretical Underpinnings

The rise of indexing stems from the Efficient Market Hypothesis (EMH) by Fama (1970), which argues that market prices fully reflect all available information. Malkiel (1995; 2003) and Fama and French (2010) provided empirical evidence that most active managers underperform passive benchmarks after fees and taxes. French (2008) quantified this underperformance at 0.67% annually—a persistent drag that supports passive strategies.

2.3.2 Growth and Cost Advantages of Indexing

The first index fund, introduced by Vanguard in 1976, and the later development of ETFs in the 1990s (Gastineau, 2001) revolutionized investing through low cost, transparency, and liquidity. Bogle (2017) emphasized that indexing reduces expenses (0.03–0.20%), improves tax efficiency, and minimizes manager risk.

2.3.3 Factor Investing and Smart Beta

Carhart (1997) introduced a four-factor model (adding momentum), showing that most fund returns can be attributed to systematic factors. This laid the groundwork for smart beta, which Arnott et al. (2016) showed can improve returns using factor tilts (e.g., value, quality, low volatility) while retaining the benefits of indexing.

2.3.4 Systemic Concerns about Passive Dominance

Scholars have raised alarms about excessive passive ownership. Wurgler (2011) and Babina et al. (2021) found that indexing distorts price discovery, as index constituents may trade based on flows rather than fundamentals. Ben-David et al. (2018) showed that ETF-driven rebalancing increases volatility during crises, and Petajisto (2017) warned of potential degradation in market efficiency.

Greenwood and Thesmar (2011) identified three systemic risks: mechanical trading, correlated ownership, and reduced active oversight—leading to greater price fragility.

2.3.5 ESG and Zero-Fee Innovations

The ESG-efficient frontier proposed by Pedersen et al. (2021) extends passive strategies into sustainable investing. Meanwhile, Huang (2022) studied the impact of zero-fee ETFs (e.g., Fidelity's ZERO funds), noting both the democratization of access and the risk of reduced innovation in fund management.

2.4 Literature on New Frontiers

2.4.1 AI and Alternative Data Integration

Recent innovations apply AI and alternative data to portfolio management. Gu et al. (2023) introduced neural portfolio networks that adapt asset weights using real-time data (e.g., sentiment, satellite imagery), outperforming traditional MVO by 4.2% annually. Dixon and Halperin (2024) implemented reinforcement learning-based rebalancing that cuts turnover costs by 30%.

2.4.2 Climate-Aware and Sentiment-Based Risk Models

Pedersen et al. (2023) created a Climate-Efficient Frontier, quantifying the return-risk impact of carbon constraints. Engle et al. (2024) developed Dynamic Climate Value-at-Risk (DCVaR), which forecasts portfolio losses under global warming scenarios. Barberis and Jin (2024) modeled investor sentiment to mitigate downside risk during panic-driven selloffs.

2.4.3 Quantum and Custom Indexing Innovations

Harrow et al. (2023) demonstrated the potential of quantum optimization, solving complex portfolio problems 100x faster than classical methods. Chinco et al. (2024) proposed AI-driven customized indices, tailored to ESG or risk preferences. In practice, BlackRock (2025) launched dynamic ETFs that adjust exposures in real time using machine learning. However, Begenau and Farboodi (2025) found that when passive ownership exceeds 50%, price efficiency falls by 18%, raising concerns about systemic vulnerabilities in markets dominated by automated flows.

3. Data and Modeling

In this paper, a constrained regression model with real-world constraints is used to estimate asset weights in the portfolio that are able to reproduce the performance of the overall index.

3.1 Data Selection and Preprocessing

In this paper, share price data of 14 companies including Fars, Vabshahr, Tapico, Tipico, Vasapa, Vama’aden, Femli, Foolad, Parsan, Sefars, Vabemellat, Vabank, Remapna, and VaGhadir, along with the overall index (as a benchmark), have been used. These companies comprised approximately 34 percent of the total market on 17 May 2025. The data is from the time each company entered the stock exchange until 17 May 2025. The reason for selecting these 14 companies is due to their fundamental conditions, being a holding and investment company, and the consideration of approximately all industries, which can be suitable for institutional investors. Table 1 shows these companies. Also, for retail investors, 5 large companies on the stock exchange, which comprise approximately 30 percent of the total market, were considered. These companies include Fars, Femli, Foolad, Vabemellat and, Nouri. Table 2 shows these companies. The risk-free interest rate was assumed to be 21 percent annually. The data was obtained through the TseClient software on the TSETMC.com website. Tables 3 and 4 show the performance of these companies from the period of listing on the stock exchange to May 17 of this year. The value of the companies was calculated at 820,000 Rials per dollar.

Table 1. The 14 Companies Mentioned

Company symbol	**Description**	**Company value on the last day- Billion Rials**	**Company value on the last day- Dollars**	**Company value ranking on the last day**
Fars	Persian Gulf Petrochemical Industries Co	9,260,000	11,292,682,927	1
Femli	National Iranian Copper Industry Co	7,549,500	9,206,707,317	2
Foolad	Mobarakeh Steel Company	5,923,500	7,223,780,488	3
Vabemellat	Bank Mellat	3,397,680	4,143,512,195	4
Parsan	Parsian Oil and Gas Development Co	2,525,580	3,079,975,610	7
VaGhadir	Ghadir Investment Holding Company	2,451,600	2,989,756,098	8
Tapico	Tamin Petroleum & Petrochemical Investment Co	2,274,615	2,773,920,732	9
Vama’aden	Mines and Metals Development Investment Company	1,099,595	1,340,969,512	26
Remapna	Mapna Group	1,012,200	1,234,390,244	29

Company symbol	Description	Company value on the last day-Billion Rials	Company value on the last day-Dollars	Company value ranking on the last day
Vabank	Tose’e Melli Group Investment Company	481,898	587,680,488	46
Sefars	Fars Cement Company	418,000	509,756,098	53
Tipico	Tamin Pharmaceutical Investment Company	353,870	431,548,780	58
Vasapa	Saipa Investment Group co.	176,020	214,658,537	118
Vabshahr	Behshahr Industries Development Group	165,250	201,524,390	122

Source: Research finding.

Table 2. The 5 Companies Mentioned

Company symbol	Description	Company value on the last day-Billion Rials	Company value on the last day-Dollars	Company value ranking on the last day
Fars	Persian Gulf Petrochemical Industries Co	9,260,000	11,292,682,927	1
Femli	National Iranian Copper Industry Co	7,549,500	9,206,707,317	2
Foolad	Mobarakeh Steel Company	5,923,500	7,223,780,488	3
Vabemellat	Bank Mellat	3,397,680	4,143,512,195	4
Nouri	Nouri Petrochemical Company Co	3,116,400	3,800,487,805	5

Source: Research finding.

Table 3. Performance of the 14 Companies Mentioned

Company symbol	Average annual return	Annual risk	Sharpe Annual
overall index	0.389	0.169	1.058
Parsan	0.523	0.324	0.966
Vabank	0.473	0.288	0.913
Vabemellat	0.465	0.319	0.800
Femli	0.447	0.298	0.797
VaGhadir	0.446	0.297	0.792
Tipico	0.419	0.270	0.759
Vama'aden	0.448	0.321	0.742
Fars	0.410	0.279	0.715
Foolad	0.427	0.307	0.708
Tapico	0.399	0.322	0.587
Remapna	0.419	0.357	0.585
Sefars	0.371	0.326	0.495
Vabshahr	0.332	0.302	0.406
Vasapa	0.367	0.434	0.363

Source: Research finding.

Table 4. Performance of the 5 Companies Mentioned

Company symbol	Average annual return	Annual risk	Sharpe Annual
Nouri	0.838	0.380	1.652
overall index	0.389	0.169	1.058
Vabemellat	0.465	0.319	0.800
Femli	0.447	0.298	0.797
Fars	0.410	0.279	0.715
Foolad	0.427	0.307	0.708

Source: Research finding.

The key implementation steps are:

- Receiving data from the TseClient software
- Preprocessing data, including removing outliers using quantiles
- Calculating asset returns
- Considering warm-up and back-test periods

- Then running the algorithm and presenting the model results.

3.2 Portfolio Construction and Optimization Techniques

The three major types of portfolios are as follows:

1. Simple (equal-weighted) portfolio

This portfolio assigns equal weights to all selected assets. This portfolio serves as a benchmark to demonstrate an uninformed but diversified strategy.

2. Mean-variance optimized portfolio

Using the Markowitz mean-variance framework, the weights of the assets are optimized to maximize the expected return for a given level of risk.

3. Indexed portfolio

This portfolio mimics a market-weighted index, such as the overall index. The weight of each asset corresponds to its proportion in the benchmark index.

In addition, alternative optimization models are as follows:

The Black-Litterman model, incorporating investor perspectives, equal risk allocation, balancing the risk contribution from each asset, and the minimum variance portfolio, focusing solely on risk minimization.

3.3 Performance Evaluation Criteria

The portfolio is evaluated using the following performance criteria:

- Annual Return: The average daily return scaled (multiplied by 252) by the annualized return.
- Annualized Volatility: The standard deviation of the daily return scaled (multiplied by the square root of 252) by the annualized return.
- Sharpe Ratio: The excess return (minus the risk-free rate) per unit of risk.
- Maximum Drawdown: The largest peak-to-trough decline in the portfolio value.
- Tracking Error: The standard deviation of the difference between the portfolio return and the index (used to compare active versus passive portfolios).
- Calmar Ratio: The excess return (minus the risk-free rate) divided by the maximum peak-to-trough.
- Statistical tests such as t-tests or bootstrap analysis are applied to assess the significance of performance differences across portfolios.

3.4 Model Used

Suppose:

$R_b \in \mathbb{R}^T$ is the vector of total index returns for period T.

$R \in \mathbb{R}^{T\times N}$ is the matrix of asset returns.

$w \in \mathbb{R}^N$ are the optimal weights of the portfolio.

$w_{\text{prev}} \in \mathbb{R}^N$ are the current weights of the portfolio.

Now the portfolio optimization problem is as follows:

$$\begin{aligned} &\min_w \|R_b - R * w\|_2^2 \\ &s \cdot t \quad \sum_{i=1}^{N} w_i = 1 \\ &\qquad l_i \le w_i \le u_i \\ &\|w - w_{\text{prev}}\|_1 \le \tau \end{aligned} \tag{1}$$

τ is limitation of asset turnover in the portfolio. Transaction costs are added to the model in two ways: one is approximated using asset turnover, and the second is deducted as a cost from the total portfolio return during each rebalancing period of the portfolio weights. For example, the total return of the portfolio is calculated as follows:

$$pret = \sum(\mu_i \cdot w_i \cdot T_e - b \cdot max(c, W_{0i} - w_i) - d \cdot max(e, w_i - W_{0i})) \tag{2}$$

where:

- μ_i is the expected return of asset,
- w_i is the portfolio weight,
- W_{0i} is the initial weight,
- and the penalty terms discourage deviations from a preferred or policy allocation.
- T_e is the investment horizon.
- C and e are vectors of zero values with the dimension of the number of assets.
- B and d are transaction costs of buying and selling.

The model is run and the weights are updated every 21 days, based on the past time window. Also, for more information, see the corresponding Python code on GitHub, in the section of “Declaration”.

3.5 Tools and Software

This analysis is implemented using Python with libraries such as NumPy, pandas, cvxpy, and statsmodels.

4. Results

This section presents the results of the empirical analysis and discusses its implications for portfolio management. In this analysis, transaction costs (0.00371 for long and 0.0088 for short), asset weight limits (minimum 1 percent and maximum 10 percent), and asset turnover in the portfolio (25 percent) are considered. First, back-tests are presented for a portfolio of 14 companies and then for the 5 companies mentioned. The balancing period of the portfolio weights is considered every 21 days and then the results are presented for 2-year and 1-year periods.

4.1 Comparing the Performance of a 14-company Stock Portfolio with the Overall Index

- 2-year period:

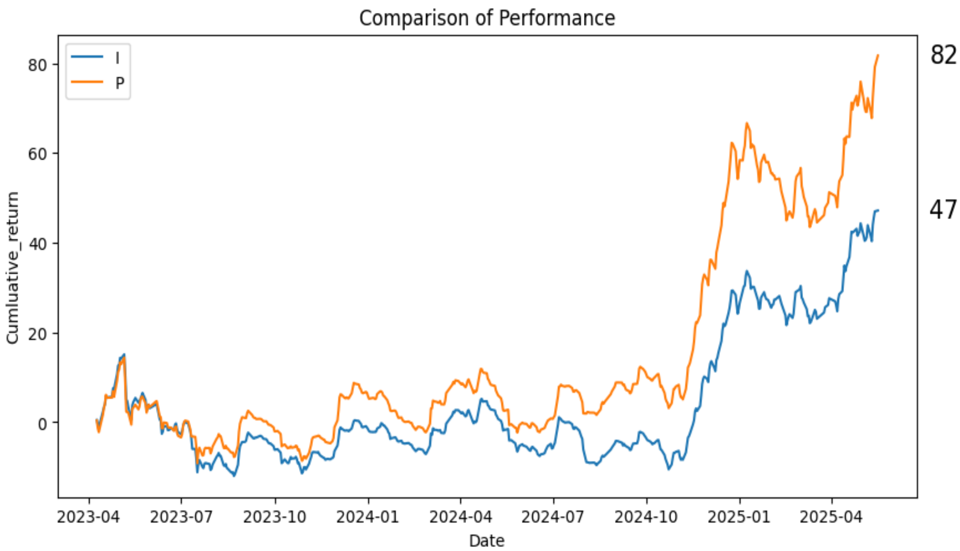

Figure 1. Comparison of Cumulative Returns of the Indexed Portfolio and the Total Index
Source: Research finding.

Comparing the cumulative returns shows that after 2 years, this rate is 82% for the portfolio and 47% for the overall index (Figure 1). As Table 5 shows, the Sharpe ratio, Sortino ratio, peak-to-trough ratio, and Kalmar ratio of the indexed portfolio are better than those of the overall index. The indexed portfolio also has a beta of 1.06.

Table 5. Comparing the Performance of the Indexed Portfolio with the Overall Index

	SHARPE	SORTINO	MAX_DRAWDOWN	CALMAR, ALPHA, BETA
INDEXED PORTFOLIO	0.56	0.81	-0.21	[0.52, 0, 1.06]
OVERALL INDEX	-0.01	-0.0136	0.24	[-0.01, -0, 1]

Source: Research finding.

The difference in returns between this model and the overall index during this period is significant, and the t-statistic is -2.58 with a significance probability of 1 percent.

$$t = \frac{\mu_{P-I}}{\sigma_{P-I}/\sqrt{N}} = -2.58$$

- One-year period:

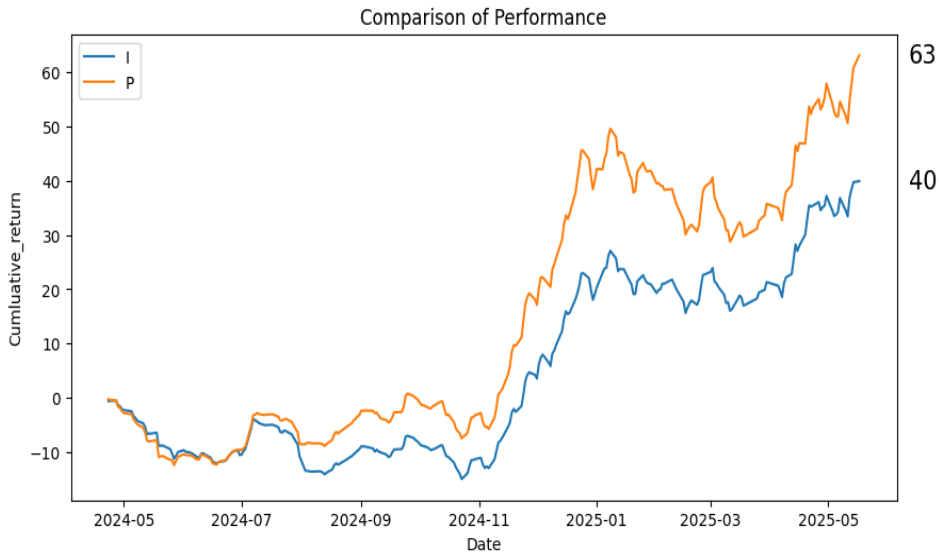

Figure 2. Comparison of Cumulative Returns of the Indexed Portfolio and the Total Index
Source: Research finding.

Comparing the cumulative returns shows that after 1 year, this rate is 63% for the portfolio and 40% for the overall index (Figure 2). As Table 6 shows, the Sharpe ratio, Sortino ratio, peak-to-trough ratio, and Kalmar ratio of the indexed portfolio are better than those of the overall index. The indexed portfolio also has a beta of 1.07.

Table 6. Comparing the Performance of the Indexed Portfolio with the Overall Index [2.16, 0, 1.07]

	SHARPE	SORTINO	MAX_DRAWDOWN	CALMAR, ALPHA, BETA
INDEXED PORTFOLIO	1.56	2.32	-0.14	[2.16, 0, 1.07]
OVERALL INDEX	0.84	1.24	-0.15	[0.98, -0, 1]

Source: Research finding.

The difference in returns between this model and the overall index during this period is significant, and the t-statistic is -2.40 with a significance probability of 1.71 percent.

$$t = \frac{\mu_{P-I}}{\sigma_{P-I}/\sqrt{N}} = -2.40$$

4.2 Comparing the Performance of a 5-Company Stock Portfolio with the Overall Index

- 2-year period:

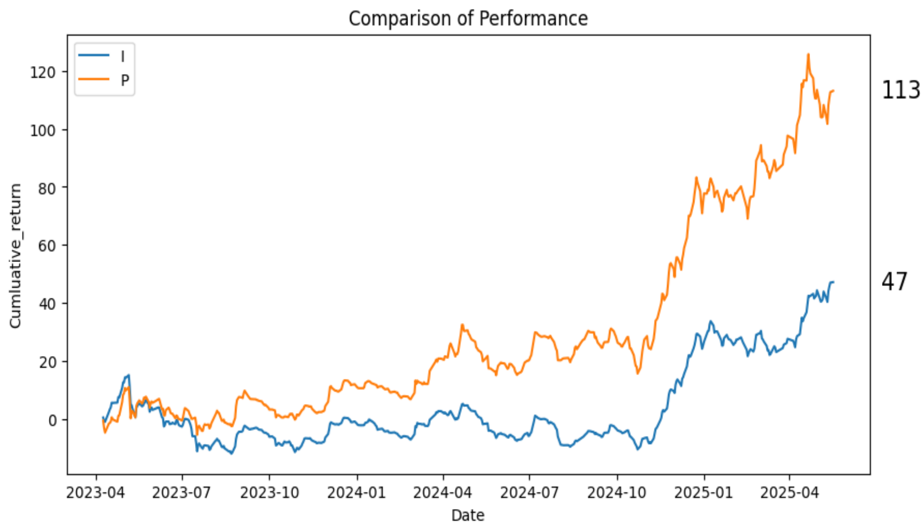

Figure 3. Comparison of Cumulative Returns of the Indexed Portfolio and the Total Index

Source: Research finding.

Comparing the cumulative returns shows that after 2 years, this rate is 113% for the portfolio and 47% for the overall index (Figure 3). As Table 7 shows, the Sharpe ratio, Sortino ratio, peak-to-trough ratio, and Kalmar ratio of the indexed portfolio are better than those of the overall index. The indexed portfolio also has a beta of 1.12.

Table 7. Comparing the Performance of the Indexed Portfolio with the Overall Index

	SHARPE	SORTINO	MAX_DRAWDOWN	CALMAR, ALPHA, BETA
INDEXED PORTFOLIO	**0.91**	**1.33**	**-0.15**	**[1.29, 0, 1.12]**
OVERALL INDEX	**-0.01**	**-0.01**	**-0.24**	**[-0.01, -0, 1]**

Source: Research finding.

The difference in returns between this model and the overall index during this period is significant, and the t-statistic is -3.07 with a significance probability of 0.2 percent.

$$t = \frac{\mu_{P-I}}{\sigma_{P-I}/\sqrt{N}} = -3.07$$

- One-year period:

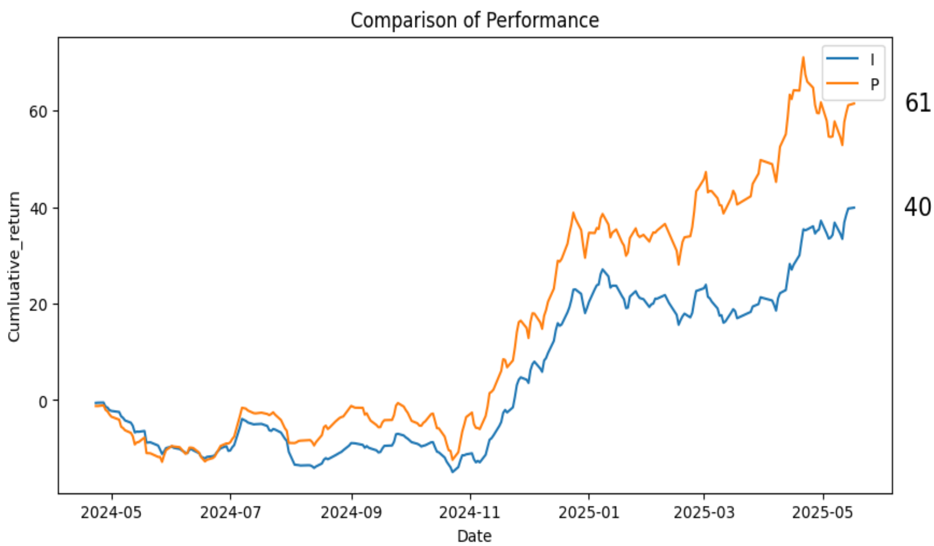

Figure 4. Comparison of Cumulative Returns of the Indexed Portfolio and the Total Index

Source: Research finding.

Comparing the cumulative returns shows that after 1 year, this rate is 61% for the portfolio and 40% for the overall index (Figure 4). As Table 8 shows, the Sharpe ratio, Sortino ratio, peak-to-trough ratio, and Kalmar ratio of the indexed portfolio are better than those of the overall index. The indexed portfolio also has a beta of 1.07.

Table 8. Comparing the Performance of the Indexed Portfolio with the Overall Index

	SHARPE	SORTINO	MAX_DRAWDOWN	CALMAR, ALPHA, BETA
INDEXED PORTFOLIO	1.36	1.97	-0.12	[2.49, 0, 1.17]
OVERALL INDEX	0.84	1.24	-0.14	[0.98, -0, 1]

Source: Research finding.

The difference in returns between this model and the overall index during this period is significant, and the t-statistic is -1.60 with a probability of 5%, one-sided, or significant at the 10% level.

$$t = \frac{\mu_{P-I}}{\sigma_{P-I}/\sqrt{N}} = -1.60$$

4.3 Implication for Investors

Indexing remains a valuable strategy for institutional investors with access to advanced tools and predictive models. Therefore, by selecting these 14 stocks (of course, periodically changing these 14 stocks) and using this indexed portfolio, these investors can outperform the overall index in the medium and long term. Of course, these investors can adjust their portfolios in different periods and with greater frequency.

For retail investors or in environments with low expected alpha, indexing offers a low-cost and tax-efficient approach that often outperforms active management. Therefore, these investors can outperform the overall index in the medium and long term by selecting these 5 stocks (of course, periodically by changing these 5 stocks) and using this index portfolio.

5. Conclusion and Suggestions

This paper investigated the theoretical foundations and empirical effectiveness of indexed portfolio construction, positioning it as a practical and cost-effective strategy for both retail and institutional investors. Drawing on a comprehensive review of literature and rigorous quantitative testing within the Iranian capital market, the study offers compelling evidence that indexing serves as a robust alternative to traditional optimization-based portfolio strategies.

Indexing provides a low-cost, transparent, and scalable approach to gaining market exposure. Particularly in emerging markets like Iran—where liquidity constraints, transaction costs, and behavioral inefficiencies are more pronounced—passive strategies can offer superior long-term performance. The indexed portfolio developed in this study outperformed the benchmark index over one- and two-year periods, even when constrained by realistic implementation conditions.

5.1 Key Contributions

This research makes the following contributions to the academic and practical discourse on portfolio management:

- Localized Application: It introduces an indexed portfolio tailored specifically to the structure and characteristics of the Iranian capital market, targeting both retail (5-stock) and institutional (14-stock) investor segments.
- Practical Constraints: It integrates real-world implementation constraints, including transaction costs, turnover limits, and weight bounds, ensuring that the proposed strategy reflects conditions investors actually face.
- Empirical Back-testing: The performance of the portfolio was tested through historical back-tests, and evaluated using statistical significance tests, specifically t-tests, to validate robustness and consistency over different horizons.

5.2 Comparative Analysis

To position this research within the broader literature, Table 9 presents a comparative evaluation of this study's methodology and findings against three well-known studies in the field.

Table 9. Comparing the Performance of the Indexed Portfolio with the Overall Index

Feature	This Paper	Beasley (2003)	Benidis (2018)	Clarke (2006)
Sample Size	5 (retail) + 14 (institutional)	50-100 stocks	50-500 stocks	100+ stocks
Optimization Method	Constrained regression	Quadratic programming	Lasso regression	Mean-variance
Rebalancing	21-day periods	Monthly	Annual	Quarterly
Constraints	Turnover, weights, costs	Weights, turnover	Sparsity, turnover	Turnover, costs
Statistical Test	t-test for significance	None	None	Sharpe ratio comparison
Outperformance	Yes (1Y & 2Y)	Yes (long-term)	Mixed results	Yes (with constraints)

Source: Research finding.

This comparison shows that while earlier studies employed more conventional optimization techniques (e.g., quadratic programming or mean-variance), this paper distinguishes itself by focusing on a constrained regression framework tailored to local conditions. Moreover, the use of t-tests for statistical evaluation strengthens the credibility of its performance claims.

5.3 Limitations and Directions for Future Research

While this study offers valuable insights, several limitations must be acknowledged:

- Limited Stock Universe: The research focuses on a relatively small sample of stocks due to data availability and implementation constraints. This limits the generalizability of findings to broader asset classes or the full market universe.
- Constraint-Driven Design: The real-world constraints (e.g., transaction costs, turnover limits, and position bounds) necessary for practical relevance also restrict the theoretical efficiency of the portfolio.
- Market-Specific Focus: The results are derived from the Iranian capital market, and while transferable insights exist, external validation in other emerging or developed markets is needed.

Building upon the findings of this study, future research may explore several promising directions:

- Machine Learning and Predictive Modeling: Employ supervised learning or reinforcement learning for expected return prediction and adaptive rebalancing strategies.
- Scenario Analysis & Stress Testing: Simulate performance under extreme market conditions (e.g., sanctions, currency devaluation) using Monte Carlo or historical scenarios.
- Comparative Strategy Analysis: Evaluate the performance of different portfolio construction frameworks such as:
  - Equal-weighting
  - Traditional mean-variance optimization
  - Black-Litterman model
  - Risk-parity strategies
- Factor-based and ESG Indexing: Extend the analysis to smart beta or ESG-based indexing, particularly relevant for institutional mandates.
- Behavioral Factors and Adoption: Study investor behavior and the barriers to widespread adoption of passive strategies in local markets.

By combining empirical analysis with practical constraints, this study demonstrates that indexed portfolio construction is not only feasible but also advantageous in emerging markets. It paves the way for future work that can build more dynamic, adaptive, and robust investment frameworks for investors across varying market environments.

Declaration

Availability of data and material: The datasets used in this study are publicly accessible on https://github.com/user-attachments/files/20634766/Adjusted.zip.
The codes used in this study are publicly accessible on https://github.com/baminro/Indexed-Portfolio/blob/main/Indexed%20Portfolio%20Codes.

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