AES
ISSN: 2096-3246
Volume 58, Issue 02, 2026

USING PCA LOADINGS AS PORTFOLIO WEIGHTS: EVIDENCE FROM THE SAUDI EQUITY MARKET (TADAWUL)

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Abstract
Portfolio construction lies at the core of modern investment management, providing a systematic framework for allocating capital across assets to optimize returns relative to risk. Traditional portfolio construction approaches, such as equal weighting or capitalization weighting, fail to adequately account for these complex interrelationships. Even conventional optimization techniques may struggle when the covariance structure among sectors is unstable or when the number of sectors approaches the number of historical observations, leading to estimation errors and suboptimal outcomes (Michaud, 1989). To address these challenges, researchers and practitioners increasingly employ data-driven techniques such as Principal Component Analysis (PCA) to extract latent factors that explain the co-movement of asset returns (Connor & Korajczyk, 1986; Pástor & Stambaugh, 2003). The primary contributions of this study are threefold. First, it enhances the understanding of sectoral dynamics within the Saudi equity market by identifying latent economic factors driving sector co-movements. Second, it demonstrates how PCA loadings can be transformed into actionable portfolio weights, offering a transparent and economically grounded alternative to conventional optimization methods. Third, it provides empirical evidence on the risk-return trade-offs of PCA-weighted portfolios relative to traditional strategies, highlighting the practical benefits and limitations of this approach.

Keywords:
Saudi Equity Market; Portfolio optimization; Principal Component Analysis (PCA); PCA Loadings; Portfolio Weights.

1. Introduction

The Saudi financial market (Tadawul) has emerged as a key player among Gulf Cooperation Council (GCC) exchanges, driven by structural reforms under Vision 2030, increased foreign investor participation, and its growing inclusion in global indices (e.g., MSCI Emerging Markets (EM)). However, Tadawul remains characterized by unique challenges: high dependence on oil prices, exposure to geopolitical shifts, and periodic volatility spikes.

Portfolio construction lies at the core of modern investment management, providing a systematic framework for allocating capital across assets to optimize returns relative to risk. Since the pioneering work of Markowitz (1952), mean-variance optimization has served as the theoretical foundation for portfolio selection, emphasizing diversification to achieve efficient risk-return trade-offs. However, practical implementation of this framework in dynamic and evolving markets—such as emerging economies proposes significant challenges due to sectoral interdependencies, structural reforms, and rapidly changing economic conditions.

The Saudi equity market, represented by the Tadawul All Share Index (TASI), offers a compelling case for advanced portfolio methodologies. As the largest and most liquid market in the Middle East,

Saudi Arabia has undergone substantial transformation under Vision 2030, a national strategy aimed at economic diversification beyond oil dependence. This transition has led to significant changes in sectoral dynamics, with new industries such as renewable energy, technology, and healthcare growing in prominence alongside traditional sectors like oil, banking, and real estate. In this context, sector-level allocation decisions require tools capable of capturing hidden relationships and common drivers of performance across industries.
Traditional portfolio construction approaches, such as equal weighting or capitalization weighting, fail to adequately account for these complex interrelationships. Even conventional optimization techniques may struggle when the covariance structure among sectors is unstable or when the number of sectors approaches the number of historical observations, leading to estimation errors and suboptimal outcomes (Michaud, 1989). To address these challenges, researchers and practitioners increasingly employ data-driven techniques such as Principal Component Analysis (PCA) to extract latent factors that explain the co-movement of asset returns (Connor & Korajczyk, 1986; Pástor & Stambaugh, 2003).

PCA is particularly valuable in identifying the underlying economic forces driving sectoral returns without imposing strict parametric assumptions. By reducing the dimensionality of the return space, PCA uncovers a smaller set of factors that capture the majority of market variance, enabling more efficient and interpretable portfolio design. However, a key limitation of traditional PCA applications in finance is that the extracted principal components are orthogonal by construction, whereas true economic factors—such as sector trends, macroeconomic shocks, and style tilts—are often correlated (Fama & French, 1993; Pukthuanthong & Roll, 2009). This orthogonality may reduce the economic interpretability of the factors and hinder their direct application to real-world portfolios.

To overcome these issues, this study applies PCA with oblimin rotation, a method that allows the factors to be correlated, thus better reflecting the interconnected nature of financial markets. Unlike conventional approaches that rely on constructing abstract factor-mimicking portfolios, this study directly converts the rotated factor loadings into sector weights, as shown in the PCA Weight (PCA Wt.) column of Table 4. This approach offers several advantages:

- It provides transparent, interpretable sector allocations that correspond to the relative importance of each sector in explaining market dynamics.
- It bridges the gap between statistical factor models and practical, tradable portfolio implementation.
- It avoids over-reliance on synthetic factors, ensuring that the portfolio remains anchored to actual sectors and investable instruments.

Using sector-level data from the Tadawul Exchange, this study constructs a PCA-weighted portfolio and compares its performance to traditional benchmarks, including equal-weighted, capitalization-weighted, optimized, risk-parity, and minimum variance portfolios. By integrating rotated PCA factor loadings directly into the portfolio weighting process, the study provides a novel, data-driven framework for allocation decisions in emerging markets.

The primary contributions of this study are threefold. First, it enhances the understanding of sectoral dynamics within the Saudi equity market by identifying latent economic factors driving sector co-movements. Second, it demonstrates how PCA loadings can be transformed into actionable portfolio weights, offering a transparent and economically grounded alternative to conventional optimization methods. Third, it provides empirical evidence on the risk-return trade-offs of PCA-weighted portfolios relative to traditional strategies, highlighting the practical benefits and limitations of this approach.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on factor modeling and portfolio construction. Section 3 outlines the methodology, including data sources, PCA application, and portfolio weighting procedures. Section 4 presents the empirical results, including sectoral correlations, rotated factor structures, and comparative portfolio performance. Section 5 concludes with implications for investors, policymakers, and future research directions.

2. Literature Review

The following section delves into the current literature review based on the following themes:

1. Foundations of Portfolio Theory and Investment Strategy

Gruber (2003) provides a foundational framework for modern portfolio theory (MPT), emphasizing the risk-return tradeoff inherent in investment decisions. MPT is rooted in the idea that investors can construct portfolios to maximize expected returns based on a given level of market risk, emphasizing diversification, historical returns, and standard deviation as key tools for optimizing asset allocations. Gruber also highlighted the influence of taxes, transaction costs, and long-term financial planning on real-world investment decisions.

Cox (2017) extends this conversation by comparing active and passive investment strategies across different markets. This study underscores the importance of market efficiency in determining the value of active management, ultimately suggesting that in highly efficient markets, passive strategies may outperform active strategies because of lower fees and predictable performance. This theoretical grounding forms the basis for evaluating dynamic portfolio strategies under volatile conditions.

2. Realized Volatility and Dynamic Portfolio Construction

In volatile markets, traditional mean-variance optimization may be insufficient. Rujivan (2025) investigates this challenge by incorporating realized volatility into equity portfolio construction using SET50 Index data. The study finds that minimizing realized volatility enhances portfolio performance and adaptability to market shocks, highlighting its value in highly unstable environments. This approach offers a data-driven alternative to variance-based methods that is suitable for both emerging and developed markets facing heightened uncertainty.

Bányai, Tatay, Thalmeiner, and Pataki (2024) further emphasize the need for active portfolio management through rebalancing. Their research over a 10-year period reveals that rebalancing can significantly enhance risk-adjusted returns, particularly for equity and commodity investments. However, they caution that certain asset classes, such as bonds and REITs, may experience diminished returns when rebalanced too frequently, suggesting a need for strategic rebalancing depending on asset characteristics and market conditions.

3. Volatility and Crisis Behavior in the Saudi Market

The Saudi stock market (Tadawul) provides a unique context for testing portfolio models under market stress. Khan (2024) analyzes Tadawul's performance during the 2007 Global Financial Crisis, revealing a sharp initial decline followed by a recovery supported by high oil prices and limited global exposure. This study demonstrates the market's resilience and the role of domestic economic fundamentals in cushioning external shocks.

Similarly, Barzanji (2021) investigates the impact of oil price fluctuations on Tadawul's performance. Her study identified a strong link between oil dynamics and investor behavior, emphasizing how commodity market dependencies can amplify volatility in oil-exporting

economies. This relationship is vital for investors and policymakers when constructing portfolios that are sensitive to macroeconomic shocks.
Syed (2019) examines intraday volatility in the Tadawul All Share Index. Using high-frequency data, this study identifies short-term patterns in price movements and trading volumes, especially during economic announcements. This microstructure-focused research underscores the importance of understanding intraday behavior when building portfolios in less-mature markets.

4. Cross-Market Dependencies and Diversification
While domestic factors play a central role, understanding global market linkages is essential for developing diversification strategies. Matar (2021) employs wavelet coherence to assess the interdependence between GCC stock markets and the U.S., finding time-varying correlations that intensify during crises. This insight supports the case for regional diversification, particularly during crisis-prone periods.
Keskinen (2024) explores how publicly available indicators such as sentiment and macroeconomic signals can anticipate market downturns. Although the focus is on the S&P 500, the methodological approach—combining sentiment analysis with economic indicators—can be applied to emerging markets such as Saudi Arabia to improve risk forecasting and strategic asset allocation.

5. Firm-Level Determinants and Value Drivers in Saudi Arabia
At the firm level, financial and operational characteristics affect portfolio outcomes. Qader (2017) evaluated the factors influencing firm value on the Tadawul using Tobin's Q. This study highlights capital structure, profitability, and corporate governance as key drivers of firm performance. These insights are critical for bottom-up portfolio-construction strategies in the Saudi market.

The literature reflects a convergence of traditional portfolio theory with modern, volatility-aware, and macro-sensitive strategies, especially in emerging markets such as Saudi Arabia. Realized volatility, oil price sensitivity, rebalancing strategy, and cross-market integration play critical roles in portfolio construction. By combining theoretical models with empirical insights specific to the Saudi market, future research can develop adaptive frameworks that better account for the region's unique economic and structural characteristics than this study.

Despite a growing body of research on portfolio construction and volatility management, there remains a significant gap in the application of advanced portfolio optimization techniques, such as realized volatility modeling, within the Saudi financial market (Tadawul). While studies such as Rujivan (2025) highlight the benefits of volatility-based optimization in other emerging markets, similar methodologies have not been widely tested in the Saudi context. Moreover, existing research often treats oil price fluctuations as external economic variables rather than directly integrating them into portfolio risk modeling or allocation strategies.

Additionally, while the global literature acknowledges the benefits of strategic rebalancing (Bányai et al., 2024), no empirical study has evaluated its effectiveness for Saudi-listed asset classes such as equities, REITs, or sukuks. The lack of adaptive portfolio frameworks that combine real-time volatility, macroeconomic signals (e.g., oil prices and interest rates), and market-specific behaviors presents a clear research opportunity. Furthermore, Saudi-focused research has largely overlooked intraday volatility dynamics and investor sentiment as practical tools for making short-term portfolio adjustments. This study seeks to fill these gaps by developing a comprehensive, Saudi-specific portfolio optimization framework that accounts for market volatility, oil price sensitivity, and rebalancing strategies tailored to the local market conditions.

3. Methodology

This section outlines the methodology, including data sources, PCA application, and portfolio weighting procedures.

3.1 Data Sources

The data for this study were obtained from the LSEG Workspace, encompassing all 20 sectors represented in the Tadawul (the Saudi Stock Exchange). The sectors included in the analysis are: Energy, Materials, Capital Goods, Commercial and Professional Services, Transportation, Consumer Durables and Apparel, Consumer Services, Media and Entertainment, Consumer Discretionary and Retail, Consumer Staples Discretionary and Retail, Food and Beverages, Health Care Equipment and Services, Pharmaceuticals and Biotechnology, Banks, Financial Services, Insurance, Software Services, Telecommunications Services, Utilities, and Real Estate Investment Trusts (REITs).

The Saudi Repo Rate, retrieved from the Saudi Arabian Monetary Authority (SAMA) website, is employed as the proxy for the risk-free rate. The sample comprises daily return data for both the Tadawul All Share Index (TASI) and its 20 sub-sectoral indices, covering the period from September 17, 2023, to August 4, 2025.

Table 1 presents the descriptive statistical characteristics of the study variables, including mean returns, standard deviations, skewness, kurtosis, and other relevant summary statistics.

Table 1 Descriptive Statistics of Study Variables

	Energy	Materials	apital_gooc	ial_profess	ansportatic	r_durables	sumer_serv	a_entertain	_discreatio	ımer_staple
Mean	5451.274	5712.682	7025.325	5036.037	6761.74	5196.652	4919.551	27379.27	7867.576	9027.406
Standard Error	24.09767	18.89552	171.2618	15.69014	39.68188	15.43781	19.47012	239.9578	19.15747	41.17718
Median	5306.185	5744.62	5208.195	5034.5	7039.68	5236.18	4966.605	29082.83	7766.485	9255.785
Mode	5313.85	#N/A	#N/A	#N/A	7517.22	5247.57	#N/A	#N/A	7547.25	#N/A
Standard Deviation	522.425	409.6452	3712.866	340.1541	860.2827	334.6838	422.1022	5202.162	415.324	892.6999
Sample Variance	272927.9	167809.2	13785376	115704.8	740086.3	112013.3	178170.3	27062490	172494.1	796913.2
Kurtosis	-0.97589	-0.80406	0.106006	0.154974	-1.32054	0.053583	-0.19069	-1.36943	-0.19863	-0.9404
Skewness	0.294522	-0.31072	1.425665	0.350633	-0.36044	-0.3174	-0.02319	-0.18616	0.707428	-0.07104
Range	2034.27	1785.5	11073.49	1855.74	3076.78	1744.8	2098.45	20759.18	1977.18	3679.65
Minimum	4531.58	4821.38	4262.16	4262.16	5019.18	4218.93	3848.35	17717.49	7021.49	7271.16
Maximum	6565.85	6606.88	15335.65	6117.9	8095.96	5963.73	5946.8	38476.67	8998.67	10950.81
Sum	2562099	2684961	3301903	2366937	3178018	2442426	2312189	12868256	3697761	4242881
Count	470	470	470	470	470	470	470	470	470	470

	od_beverag	_care_Equ	ma_biotec	Banks	ancial_servi	Insurance	ware_servi	ele_service	Utilities	Reits	si_main_Ind
Mean	5829.602	12069.28	4922.68	11930.85	7310.765	9744.316	74538.96	7975.02	11854.21	3296.28	11776.83
Standard Error	20.55608	52.09823	17.92836	34.20691	32.17306	50.66863	334.791	23.8497	110.8339	9.807977	26.03363
Median	5902.98	12248.32	4895.835	12010.02	7531.465	9768.295	75266.22	7976.235	12347.55	3269.33	11888.11
Mode	5843.39	#N/A	#N/A	#N/A	7710.86	#N/A	69605.84	#N/A	#N/A	2975.67	#N/A
Standard Deviation	445.6452	1129.463	388.6775	741.5882	697.4953	1098.47	7258.095	517.0491	2402.821	212.6319	564.3956
Sample Variance	198599.7	1275686	151070.2	549953.1	486499.6	1206636	52679945	267339.8	5773548	45212.31	318542.4
Kurtosis	-0.45779	-0.91162	0.054784	0.627699	-1.05375	-1.12196	-0.75593	-0.15021	-1.32178	-1.16888	-0.57327
Skewness	-0.28194	-0.13933	-0.13973	-0.92777	-0.26438	-0.15787	-0.35612	0.118422	-0.08037	0.110653	-0.52017
Range	2009.36	4449.74	2108.6	3605.11	2832.09	4321.85	31936.35	2568.43	8752.51	773.6	2542.46
Minimum	4790.47	9701.27	3824.35	9601.32	5862.01	7688.76	58232.83	6758.64	7650.11	2902.08	10293.19
Maximum	6799.83	14151.01	5932.95	13206.43	8694.1	12010.61	90169.18	9327.07	16402.62	3675.68	12835.65
Sum	2739913	5672563	2313660	5607498	3436060	4579829	35033313	3748259	5571479	1549251	5535109
Count	470	470	470	470	470	470	470	470	470	470	470

3.2 Analytical Methods

3.2.1 Factor Analysis Model

This study employs factor analysis and portfolio optimization techniques to examine and compare the diversification potential and performance of factor-based portfolios and sector-based portfolios. Factor analysis is applied to the 20 Tadawul sector indices to identify the underlying common factors that explain the co-movement of sector returns.

The factor model is specified as follows:

$$X_i - \mu = LF_i + \epsilon_i$$

- X_i is the v×1vector of observed variables (sector returns) for observation i,
- μ is the v×1 vector of means of the observed variables,
- L is the v×m factor loading matrix,
- F_i is the m×1 vector of unobserved standardized common factors, and
- ϵ_i is the v×1 vector of unique error terms.

Following the methodology of Anderson and Rubin (1956) and Harman (1976), the number of factors to retain is determined using a minimum eigenvalue threshold of 0.8, ensuring that only factors explaining a meaningful proportion of the variance are included.

3.2.2 Factor Extraction and Rotation

To identify the latent factors, we employ Principal Component Analysis (PCA) as the extraction method. PCA provides a data-driven approach that captures the maximum variance in the observed sector return series without imposing prior structural assumptions.

However, the initial principal components are often difficult to interpret because they are purely statistical constructs. To address this, we apply the oblimin rotation method, which allows for correlated factors, thereby reflecting the interdependencies commonly observed among economic, sectoral, and market-wide forces in financial markets.

The combination of PCA and oblimin rotation serves two key purposes:

- *Improved Interpretability*: The rotated factors align more closely with economically meaningful constructs such as sector or style effects.
- *Realistic Representation*: By permitting factor correlations, the model better reflects the interconnected nature of financial markets, where factors like momentum, value, and sector exposure often overlap.

The rotated factor scores are then used to construct the factor-based portfolios, providing a robust framework for comparing them with traditional sector-based portfolios.

3.3 Portfolio Construction and Optimization

To evaluate portfolio performance, this study applies a range of portfolio optimization strategies. The equally weighted (1/N) strategy is adopted as the benchmark, following DeMiguel, Lorenzo, and Raman (2009), who demonstrate that this simple allocation rule is difficult to consistently outperform across various market conditions.

In addition to the Equal Weight Portfolio (EWP) benchmark, three widely recognized portfolio optimization approaches are implemented to assess their diversification benefits and risk-adjusted performance:

1. Risk Parity (RP) Strategy
   - A risk-based allocation method that assigns portfolio weights to equalize the risk contributions of all assets.
   - This approach does not rely on expected return estimates and promotes balanced diversification.
2. Minimum Variance Portfolio (MVP)
   - A risk–return-based optimization technique that minimizes overall portfolio volatility.
   - This method focuses exclusively on the covariance structure of asset returns, without considering expected returns.
3. Maximum Sharpe Ratio Portfolio (MSR)
   - A risk–return-based approach that seeks to maximize the Sharpe ratio, optimizing the trade-off between expected return and risk.

- The objective is to achieve the most efficient risk-adjusted performance among all feasible portfolios.

These three methods capture a spectrum of portfolio construction philosophies, ranging from purely risk-based allocation (RP) to variance minimization (MVP) and, finally, full risk–return optimization (MSR).

Performance was evaluated using:

- Annualized Return
- Annualized Risk
- Adjusted Sharpe Ratio

This comparison highlights whether PCA-based weighting provides superior diversification and risk-adjusted returns relative to conventional approaches.

By integrating statistical factor identification techniques with portfolio optimization frameworks, this study provides a comprehensive comparison between factor-based and sector-based allocation strategies. The methodology allows for the evaluation of how different approaches to portfolio construction influence diversification and performance within the context of the Saudi equity market.

4. Results and Discussions:

This section presents empirical results, including sectoral correlations, rotated factor structures, and comparative portfolio performance. The empirical results provide a comprehensive analysis of sectoral indices from the Saudi Exchange (Tadawul), culminating in the development of a factor-based portfolio strategy.

Table 1 presents the descriptive statistics for the 20 Tadawul sector indices.

Sectoral Indices	Mean Return	SD
Energy	-0.06%	0.79%
Materials	-0.04%	0.96%
Capital_goods	0.41%	8.45%
commercial_professional_svc	-0.01%	1.51%
Transportation	0.00%	1.33%
Consumer_durables_apparel	0.01%	1.39%
Consumer_services	-0.03%	1.22%
Media_entertainment	-0.01%	2.17%
Consumer_discreationary_retail	0.00%	0.93%
Consumer_staplesD_R	-0.06%	0.95%
Food_beverages	-0.03%	1.17%
Health_care_Equip_Svc	0.01%	1.27%
Pharma_biotech_LS	0.02%	1.78%
Banks	0.04%	1.14%
Financial_services	-0.01%	1.26%
Insurance	0.02%	1.53%
Software_services	0.03%	1.62%
Tele_services	0.04%	1.06%

The analysis highlights substantial heterogeneity in both average returns and volatility across

Utilities	0.03%	2.11%
Reits	-0.04%	0.49%
Overall Mean	**0.02%**	**1.66%**
Min	**-0.06%**	**0.49%**
Max	**0.41%**	**8.45%**

sectors. The mean daily returns ranged from -0.06% to 0.41%, with Capital Goods exhibiting the highest return (0.41%) and Energy and Consumer Staples showing negative returns (-0.06%).

Volatility levels also varied considerably, with Capital Goods demonstrating the highest standard deviation (8.45%), indicating a high degree of sector-specific risk, while Reits exhibited the lowest volatility at 0.49%.

The variation across sectors confirms the need for a systematic, data-driven approach to allocate capital effectively across industries rather than relying solely on equal or market-cap weights.

4.1. Factor Analyses

Principal Component Analysis (PCA) was applied to the correlation matrix to uncover the underlying structure driving co-movements among sectors. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.957, indicating excellent suitability for factor analysis (Table 2). All individual sector MSAs exceeded the recommended threshold of 0.70, confirming strong interrelationships among the data.

Table 2

Kaiser-Meyer-Olkin Test

	MSA
Overall MSA	0.957
Banks	0.936
Capital_goods	0.745
Consumer_discreationary_retail	0.963
Consumer_durables_apparel	0.956
Consumer_services	0.95
Consumer_staplesD_R	0.96
Energy	0.927
Financial_services	0.96
Food_beverages	0.97
Health_care_Equip_Svc	0.97
Insurance	0.969
Materials	0.957
Media_entertainment	0.963
Pharma_biotech_LS	0.971
Reits	0.97
Software_services	0.95
Tele_services	0.944
Transportation	0.962
Utilities	0.939
commercial_professional_svc	0.967

From the PCA, three principal components were initially extracted, representing the latent dimensions of sectoral performance. To improve interpretability, an oblimin rotation was employed, as shown in Table 3. Unlike orthogonal rotations, which assume independent factors, oblimin allows the factors to be correlated—an important consideration in finance, where economic drivers often overlap.

- RC1 primarily loaded on consumer and service-oriented sectors, such as Consumer Durables (0.816), Consumer Services (0.815), and Transportation (0.809).
- RC2 captured financial and infrastructure sectors, with high loadings for Banks (0.777), Telecommunication Services (0.725), and Energy (0.635).
- RC3 was dominated by Capital Goods (0.926), reflecting a distinct industrial and capital expenditure theme.

These results align with the structure of the Saudi economy, which is currently transitioning under Vision 2030, emphasizing diversification beyond oil revenues, growth in domestic demand, and expansion of capital-intensive industries.

Table 3

Component Loadings

	RC1	RC2	RC3	Uniqueness	**PCA Wt.**
Consumer_durables_apparel	0.816			0.428	4.6%
Consumer_services	0.815			0.307	3.3%
Transportation	0.809			0.341	3.7%
commercial_professional_svc	0.798			0.392	4.2%
Pharma_biotech_LS	0.705			0.527	5.7%
Consumer_staplesD_R	0.702			0.427	4.6%
Media_entertainment	0.607			0.656	7.1%
Consumer_discreationary_retail	0.589			0.417	4.5%
Insurance	0.579			0.507	5.5%
Financial_services	0.432	0.419		0.418	4.5%
Reits	0.429			0.679	7.4%
Materials	0.423	0.433		0.398	4.3%
Banks		0.777		0.381	4.1%
Tele_services		0.725		0.407	4.4%
Energy		0.635		0.552	6.0%
Software_services		0.511		0.567	6.1%
Utilities		0.465		0.689	7.5%
Health_care_Equip_Svc		0.434		0.466	5.0%
Food_beverages		0.414		0.543	5.9%
Capital_goods			0.926	0.132	1.4%
					100.0%

Note. Applied rotation method is oblimin.

Rather than directly constructing portfolios using the three extracted factors, the rotated component loadings were translated into portfolio weights for each sector. This approach ensures that sector allocations reflect their proportional contributions to the identified factors while preserving economic interpretability.

The PCA Weight (PCA Wt.) column in Table 3 was calculated by normalizing the absolute factor loadings across all sectors so that the total sum of weights equals 100%. This produced a set of sector allocations that can be directly implemented as a factor-based portfolio.

For example:

- Consumer Staples (4.6%), Transportation (3.7%), and Commercial Professional Services (4.2%) received moderate weights, reflecting their significance in RC1.
- Telecommunication Services (4.4%), Banks (4.1%), and Energy (6.0%) received notable allocations under RC2.
- Capital Goods received a much smaller allocation (1.4%) due to its unique factor exposure in RC3.

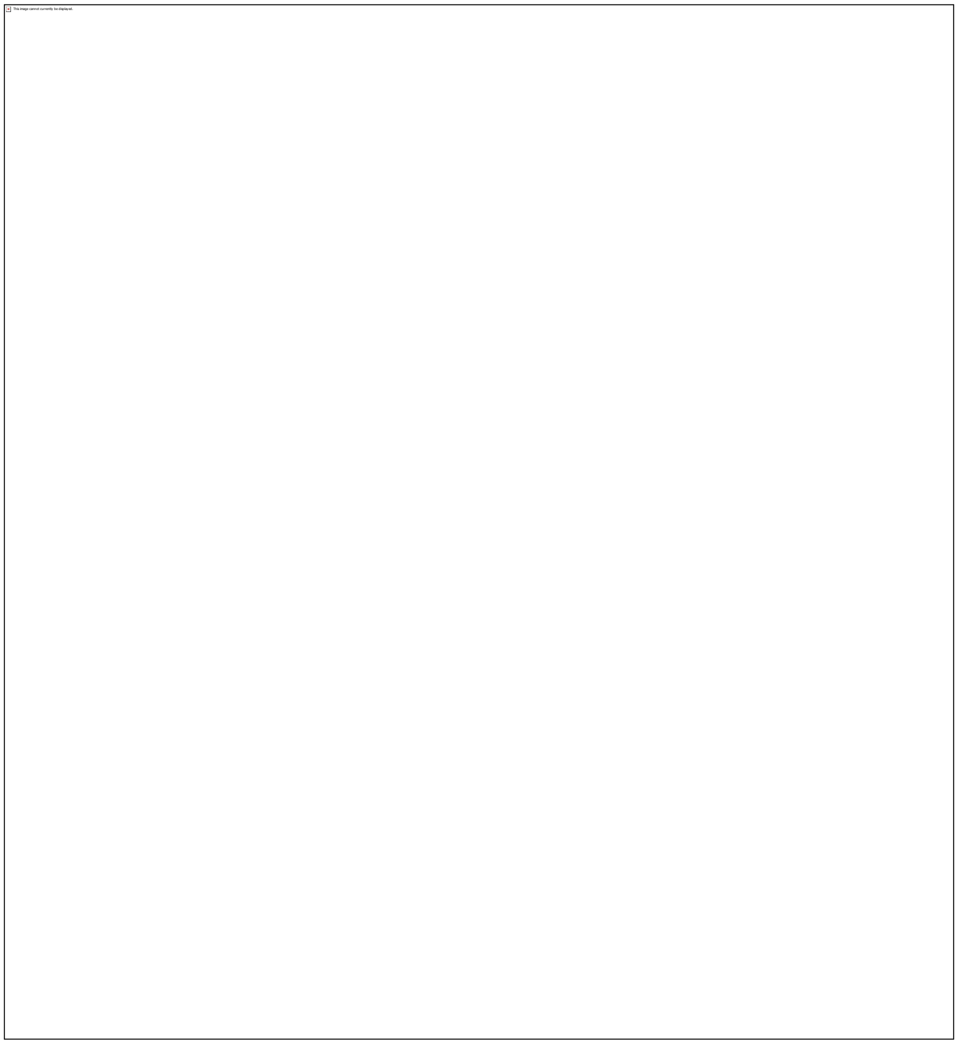

Figure 1 Path Diagram

Figure 1 graphically illustrates the relationship between the three rotated factors and the sectoral indices. The visualization confirms the clustered nature of sector loadings, with RC1, RC2, and RC3 forming distinct but interconnected groups. The use of oblimin rotation enhances interpretability, clearly showing overlapping influences among certain sectors—a realistic reflection of financial market interdependencies.

This method addresses a common limitation of traditional PCA approaches, which focus solely on abstract factor portfolios that may lack practical implementation. By using the loadings as direct weights, the portfolio design remains both statistically sound and economically meaningful, linking allocation decisions to underlying sector dynamics.

Portfolio Return= $\sum w_i \times \bar{R}_i$

Portfolio Risk=sqrt $[w^{T} \Sigma w]$

Where:

w_i = PCA weight of sector i

$\bar{R}_i$ = mean return of sector i

Σ = covariance matrix of sector returns

This approach ensures that the risk and return estimates reflect the actual PCA-based portfolio rather than an abstract factor representation. As a result, the portfolio can be directly benchmarked against traditional sector-weighted, equal-weighted, or optimized portfolios to evaluate its performance. By using PCA weights rather than abstract factor scores, the resulting portfolio provides a clear and actionable path for managing risk and return within the Saudi equity market. This represents a significant contribution to portfolio management practice, particularly in emerging markets where traditional benchmarks may not fully capture evolving sectoral dynamics.

4.2 Comparative Analysis of Portfolio Performance

We evaluate the performance of five distinct portfolio construction methodologies applied to the Saudi stock market, represented by the Tadawul sectoral indices. These methodologies include: Equal Weight Portfolio (EWP), Optimized Weight Portfolio (OWP), Principal Component Analysis Sector Portfolio (PCA-WP), Risk-Parity Portfolio (RPWP), and Minimum Variance Portfolio (MVP). The performance of each strategy is benchmarked against TASI, the market capitalization-weighted index of the Saudi Exchange.

Table 4 Summary of portfolio performance across alternative weighting schemes and TASI benchmark.

Metric	Equal Weight Portfolio	Optimized Weight Portfolio	PCA Sector Portfolio	Risk-Parity Portfolio	Minimum Variance Portfolio	TASI (Benchmark)
Annualized Return	4.21%	14.74%	3.34%	**26.79%**	**-2.51%**	-0.45%
Annualized Risk	15.5%	20.6%	15.2%	**37.5%**	**11.4%**	13.0%
Adjusted Sharpe Ratio	0.27	**0.72**	0.22	0.71	-0.22	-0.04

Table 4 summarizes the findings, providing daily and annualized portfolio returns, risk measures, and adjusted Sharpe ratios. Sector weights were optimized under realistic diversification constraints, with a minimum sector weight of 1%, maximum sector weight of 10%, and a total weight summing to 100%.

The performance outcomes highlight several key insights regarding the efficiency and risk-return profiles of the various strategies.

Risk-Parity Portfolio (RPWP).

The RPWP achieved the highest annualized return (26.79%), substantially exceeding both traditional and optimized strategies. However, this superior return came at the cost of exceptionally high volatility, with an annualized risk of 37.5%, more than double that of the Equal Weight and PCA portfolios. This behavior reflects the inherent design of risk-parity allocations, which equalize the marginal contribution of each sector to total portfolio risk, leading to overweighting of lower-volatility sectors and aggressive exposure to high-return, high-volatility sectors. While the RPWP delivered a Sharpe Ratio of 0.71, nearly identical to the optimized portfolio, the elevated risk level may render it unsuitable for investors with moderate or conservative risk appetites.

Optimized Weight Portfolio (OWP).
The OWP demonstrated strong absolute performance, producing a 14.74% annualized return with an annualized risk of 20.6%. Crucially, it recorded the highest risk-adjusted performance with a Sharpe Ratio of 0.72, slightly outperforming the RPWP. This result underscores the effectiveness of constrained mean-variance optimization, which balances expected return maximization with diversification constraints to mitigate concentration risk. The OWP's superior Sharpe Ratio suggests that active optimization under realistic constraints offers an optimal trade-off between return and volatility, aligning with modern portfolio theory (Markowitz, 1952).

Equal Weight Portfolio (EWP).
The EWP achieved a modest annualized return of 4.21% with a corresponding risk of 15.5%, leading to a Sharpe Ratio of 0.27. Although this approach lacks sophistication, it outperformed the TASI benchmark (-0.45% return, -0.04 Sharpe Ratio), reinforcing prior findings that naive diversification can enhance performance in emerging markets (DeMiguel et al., 2009). Nevertheless, the strategy's lower risk-adjusted performance highlights the opportunity cost of not leveraging optimization or factor-based allocation methods.

PCA Sector Portfolio (PCA-WP).
The PCA-WP, designed to capture latent sectoral relationships via principal component analysis, underperformed relative to both the EWP and OWP, generating an annualized return of 3.34% and a Sharpe Ratio of 0.22. While its annualized risk (15.2%) was slightly below that of the EWP, the strategy failed to translate its factor-based structure into superior returns. This outcome may be attributed to limitations in factor identification, rotation methodology, or insufficient alignment between statistical factors and economically meaningful drivers of sector performance. As such, further refinement in factor extraction and rebalancing frequency is warranted.

Minimum Variance Portfolio (MVP).
The MVP achieved the lowest risk level (11.4%), confirming its effectiveness in minimizing portfolio volatility. However, this came at a substantial cost to performance, with a negative annualized return (-2.51%) and a negative Sharpe Ratio (-0.22). These findings highlight a critical limitation of variance-focused strategies: minimizing volatility alone does not ensure adequate return generation. In declining or low-growth markets, such strategies may overly concentrate in defensive sectors, sacrificing upside potential.

TASI Benchmark.
The TASI market index delivered a negative return (-0.45%) with moderate volatility (13.0%). Its Sharpe Ratio of -0.04 indicates that passive exposure to the Saudi market during the study period failed to provide adequate compensation for risk, thereby emphasizing the necessity of active portfolio management.

Risk-Return Visualization and Trade-offs
The risk-return scatter plot (Figure 2) illustrates the positioning of the strategies:

Figure 2 Risk-return scatter plot

- The RPWP occupies the top-right quadrant, denoting high return potential coupled with high risk.
- The OWP is positioned slightly below and to the left of RPWP, indicating efficient return generation with more controlled volatility.
- EWP and PCA-WP cluster together in the center, offering moderate risk and return outcomes.
- The MVP appears in the bottom-left quadrant, signifying minimal risk but negative return potential.
- The TASI benchmark remains below the efficient frontier, reinforcing its inferior performance relative to all active strategies.

These placements highlight the diverse trade-offs between risk management and return maximization, providing critical insights for investors with heterogeneous preferences.

Sharpe Ratio and Efficiency Analysis

- The Sharpe Ratio, a key metric for assessing risk-adjusted performance, provides a holistic view of portfolio efficiency:
- The OWP's Sharpe Ratio of 0.72 demonstrates its dominance in balancing return and risk, aligning with the theoretical optimal point on the efficient frontier.
- The RPWP's similar Sharpe Ratio (0.71) suggests that, despite its high raw return, its excess volatility detracts from proportional efficiency gains.
- The EWP and PCA-WP exhibit moderate but positive Sharpe Ratios (0.27 and 0.22, respectively), reflecting partial diversification benefits relative to the benchmark.

In contrast, both the MVP and TASI record negative Sharpe Ratios, indicative of underperformance in both absolute and risk-adjusted terms.

5. Conclusion

This study examined the comparative performance of five portfolio construction methodologies—Equal Weight, Optimized Weight, PCA-based Sector Weighting, Risk-Parity, and Minimum Variance—using sectoral indices from the Saudi Stock Exchange (Tadawul). By benchmarking these strategies against the TASI market index, the analysis provides evidence on the efficacy of both traditional and data-driven approaches in an emerging market context.

The results demonstrate that active, optimization-based strategies substantially outperform passive benchmarks. Among the strategies tested, the Optimized Weight Portfolio (OWP) achieved the highest risk-adjusted performance, confirming the theoretical propositions of modern portfolio theory (Markowitz, 1952). In contrast, the Risk-Parity Portfolio (RPWP) generated exceptionally high absolute returns but with substantially elevated volatility, illustrating the inherent trade-off between return maximization and risk control. While the Equal Weight Portfolio (EWP) provided moderate gains over the market index, the Principal Component Analysis Portfolio (PCA-WP) underperformed, indicating that statistical factor extraction requires refinement to translate into economically meaningful sector allocations. Finally, the Minimum Variance Portfolio (MVP) minimized risk effectively but sacrificed return potential, demonstrating the pitfalls of focusing exclusively on volatility reduction.

A notable insight relates to the limitations of PCA in financial applications. PCA decomposes return series into orthogonal, uncorrelated components by design. While this property facilitates mathematical tractability and aids in variance decomposition, it introduces a conceptual challenge: true economic risk factors are rarely independent. Sector tilts often co-move with broader macroeconomic drivers, such as monetary policy shifts, oil price movements, or investor sentiment, and are inherently correlated with style exposures like growth versus value. By forcing orthogonality, PCA can inadvertently suppress realistic multi-factor interactions, resulting in factors that are statistically valid but economically ambiguous or difficult to interpret. This limitation may partially explain the PCA-WP's inferior performance relative to optimization-based portfolios, as the extracted components may not align with persistent, economically grounded sources of risk and return.

These findings have several practical implications. First, optimization-based portfolios, particularly those with constraints reflecting real-world investability, offer investors a robust frameork for balancing return generation with diversification. Second, while PCA remains a valuable tool for data-driven factor discovery, it must be complemented by domain knowledge and rotation techniques (e.g., oblimin rotation) that allow for correlated factors, improving interpretability and economic relevance. Third, the underperformance of passive and minimum variance strategies highlights the need for active management in emerging markets, where structural inefficiencies and concentrated sector dynamics create opportunities for alpha generation.

For future research, there is significant scope to enhance factor-based approaches by integrating machine learning, Bayesian shrinkage techniques, or dynamic factor models that explicitly allow for correlated factors and time-varying relationships. Additionally, incorporating macro-financial variables and market microstructure data may improve factor interpretability and predictive power.

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