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Evaluating Portfolio Allocation Strategies of Sovereign Wealth Funds: A Comparative Analysis of Alternative Optimization Techniques

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Abstract

Purpose: This paper applies portfolio optimization techniques to the asset allocations of Sovereign Wealth Funds (SWFs).

Methodology: Using a dataset of assets under management (AUM) values from 21 major SWFs during the period 2010–2024, we evaluate the effectiveness of four optimization strategies: minimum variance portfolio (MVP), maximum Sharpe ratio (MSR), risk parity (RP), and conditional value-at-risk (CVaR). Each model incorporates allocations to long-term average AUM weights, thereby reflecting institutional inertia and capital constraints.

Findings: The findings demonstrate that MSR and CVaR strategies outperform the others based on risk-adjusted returns, while MVP ensures portfolio stability and RP facilitate risk diversification.

Unique Contribution to Theory, Practice and Policy: These results have significant implications for the construction of robust SWF asset allocation frameworks and contribute to the broader debate on optimal portfolio design under institutional constraints.

Keywords: *Sovereign Wealth Funds, Portfolio Optimization, Minimum Variance Portfolio, Maximum Sharpe Ratio, Risk Parity, Conditional Value-at-Risk*

1. Introduction

Sovereign Wealth Funds (SWFs) are among the most influential institutional investors globally, managing vast pools of capital on behalf of future generations. Their mandates vary widely—from fiscal stabilization to intergenerational wealth preservation and economic development—but all require careful asset allocation under uncertainty. Traditional approaches to portfolio optimization, such as mean-variance analysis, provide a baseline; however, they often fail to accommodate the unique constraints and objectives of SWFs, including long-term horizons, illiquidity, and political considerations. Recent literature has proposed alternative methods such as Risk Parity, Conditional Value-at-Risk, and robust optimization techniques, which prioritize tail-risk control, risk diversification, and stability under estimation error. Yet, limited empirical work has explored these models specifically in the context of SWFs.

This paper addresses this gap by applying and comparing four prominent portfolio optimization strategies—MVP, MSR, RP, and CVaR—using a comprehensive dataset of annual AUM data from 2010 to 2024. By grounding the analysis in institutional data and incorporating regularization anchored to average AUM weights, we provide a novel and policy-relevant perspective on strategic asset allocation for sovereign funds.

The rest of the paper is made up of the following sections: Section 2 reviews the relevant literature, Section 3 discusses the data and methodology employed, Section 4 presents and analyzes the results, and Section 5 concludes the paper.

2. Literature Review

A growing body of research has examined portfolio design strategies for Sovereign Wealth Funds (SWFs), yet few studies have incorporated fund size—typically measured by assets under management (AUM)—directly into formal portfolio optimization models. For instance, Ma et al. (2016) empirically investigated SWF asset allocations and highlighted the influence of policy objectives and institutional flexibility. However, their analysis stopped short of embedding AUM into a quantitative optimization structure. Behrendt (2013) approached asset allocation from a strategic governance perspective, noting that larger fund size tends to shift liquidity preferences and risk appetite, yet did not operationalize those dynamics in a model-based framework. Similarly, Bortolotti, Fotak, and Megginson (2015) emphasized the importance of scale in shaping fund behavior, including diversification and geopolitical engagement, but without incorporating AUM into the mathematical formulation of portfolio allocation.

Historically, portfolio optimization approaches are rooted in Markowitz's (1952) mean-variance framework, which seeks to minimize portfolio risk for a given level of expected return. Sharpe's (1966) development of the Sharpe ratio introduced a risk-adjusted return measure, forming the basis for maximum Sharpe ratio (MSR) strategies. More recent innovations include risk parity (RP), which equalizes marginal risk contributions across assets, and conditional value-at-risk (CVaR), which emphasizes downside risk control and tail-event sensitivity.

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Despite these advancements, most optimization frameworks applied to SWFs have treated AUM as exogenous, rather than as a parameter influencing asset allocation directly. This represents a key limitation, as fund size can materially affect risk tolerance, rebalancing frequency, liquidity constraints, and the ability to access certain asset classes. Our study addresses this gap by explicitly integrating AUM sensitivity into all four optimization models—MVP, MSR, RP, and CVaR—allowing us to explore how fund scale alters optimal portfolio structures. This innovation adds practical relevance for sovereign asset managers tasked with designing size-appropriate, scalable allocation policies.

Penayo, Pribičević, and Novak (2025) compare six asset allocation strategies—four MV configurations and two RP-based approaches—against an equally weighted benchmark, using 111 stocks from the NASDAQ-100 and NASDAQ Financial-100 indices over 2000–2019. They introduced a combination of econometric and machine learning (ML) forecasts for returns and volatility and used a variation of RP. Scenario testing results show that their "ML-enhanced Maximum Sharpe Ratio (MSR) strategy achieves up to 1490% higher Return on Investment (ROI) than the benchmark and 1390%–1909% higher than alternative strategies, competitive Normalized Mean-Square Error (NMSE) values confirm its robustness in forecasting noisy data; ML approaches exhibit sensitivity to training data, with compound annual returns declining by up to 5.24% under alternative training periods, reflecting macroeconomic regime-switching effects; and (iv) while ML methods often produce higher absolute returns, they do not consistently yield improved risk-adjusted performance, with non-ML strategies sometimes matching or surpassing ML Sharpe Ratios (SR)".

According to Bortolotti, Loss, and Van Zwieten (2023), the empirical results related to SWFs show that over the last five years, there has been an increased investment in their sustainable development goals (SDGs). From 2018 onwards, momentum has been building in portfolio allocation covering climate and energy, especially in deal value. Investing in the agriculture sector, and to a certain extent in the education sector, started picking up in 2020. Their research provides descriptive evidence showing that the presence of explicit environmental, social, and governance (ESG) policies in place favor capital deployment aligned with SDGs. "The research shows that studies the ESG performance of a sub-sample of listed firms that SWFs have invested in, finding a significant deterioration in the governance pillar. This result is broadly consistent with previous research on the agency costs of sovereign ownership. The paper concludes by making policy recommendations regarding fiduciary duty, investee corporate governance, and climate investments, which would contribute to modernizing the role of SWFs in the global economy".

Sheng, Chen, Chen, and An (2025) address a dynamic portfolio optimization by integrating machine learning (ML) into a risk parity model based on conditional value-at-risk (CvaR-RP). This was done with the objective of enhancing the CVaR-RP's predicting accuracy and adaptability to changing market conditions. Subsequent results show that the CVaR-RP strategy outperforms volatility-based risk parity and equal-weight strategies.

Gurnin's (2024) study integrates credit risk and interest rate risk as risk measures in bond portfolio optimization, contrasting them with standard deviation, using Markowitz's (1952) Mean-Variance (MV) Optimization and introduces an optimization technique called Duration Spread Ratio (DSR) optimization. This technique combines duration and spread as risk measures. The research is based on U.S. corporate bond indices and employs a robust experimental design to compare the out-of-sample performance of portfolios created using DSR optimization and those constructed using MV optimization. The empirical results show that DSR optimization generated different results from those generated via the MV optimization in all scenarios researched.

McGrath (2025) attempts to establish stabilization mechanisms for different resource-rich countries with SWFs, addressing national economic stability, especially healthcare financing. "Despite their vast financial resources and long-term investment horizons, SWF investments in healthcare often lack structured frameworks that align with host country governance, economic priorities, and healthcare needs. Existing literature provides limited guidance on optimizing SWF healthcare investments to achieve both financial sustainability and socio-economic impact. This study addresses this gap by developing and empirically validating a conceptual model that integrates SWF investment strategies, host country governance quality, economic classifications, and healthcare priorities"

3. Data and Methodology

This study examines the risk characteristics and diversification potential of SWFs over the period 2010–2024, based on a custom panel dataset comprising 21 SWFs from diverse geographical, institutional, and economic backgrounds. The SWFs selected represent a mix of pension/savings funds, stabilization funds, strategic investment funds, and endowment-like structures, with funding sources ranging from oil and gas revenues, foreign exchange reserves, and fiscal surpluses to state-owned enterprise holdings and tobacco settlements. The funds represent both commodity-based and non-commodity-based sovereign investors, allowing for meaningful cross-fund comparison.

3.1 Sample Selection

The SWFs included in the analysis are listed in Table 1. The sample covers a broad geographic distribution across Europe, Asia, the Middle East, North America, and Oceania, and reflects substantial heterogeneity in institutional mandates, funding sources, and investment objectives. While several entities in the sample are sub-national funds or public endowments (e.g., U.S. state permanent funds and public university endowments), they are commonly treated as sovereign or sovereign-like investors in the empirical literature due to their scale, long-term investment horizons, and public ownership structure.

3.2 Funding Sources and Industry Classification

Each fund is classified according to its primary funding source, which serves as a proxy for the dominant economic sector supporting the fund. In particular, SWFs are categorized into:

- Commodity-based funds, primarily financed by oil, gas, and mineral revenues (e.g., Norway Government Pension Fund Global, Abu Dhabi Investment Authority, Alaska Permanent Fund).
- Non-commodity-based funds, funded mainly through foreign exchange reserves, fiscal surpluses, or state-owned enterprise revenues (e.g., China Investment Corporation, Temasek Holdings, Korea Investment Corporation).

This classification is essential, as prior research suggests that commodity-funded SWFs exhibit stronger intergenerational savings motives and greater exposure to global macroeconomic cycles, while non-commodity-based funds tend to pursue more conservative stabilization or reserve-management objectives.

This study evaluates the effectiveness of the following four portfolio optimization frameworks: Minimum Variance Portfolio (MVP), Maximum Sharpe Ratio (MSR), Risk Parity (RP), and Conditional Value-at-Risk (CVaR). As mentioned in earlier section of this paper, the data covers portfolios of 21 Sovereign Wealth Funds (SWFs) listed in Table 1. The investment horizon spans from 2011 to 2024. A key innovation of this analysis is the incorporation of fund-specific characteristics, particularly Assets Under Management (AUM), into each model to reflect the practical constraints and opportunities that fund size imposes on asset allocation.

The following four specific portfolio optimization models were used:

a. Minimum Varinace Portfolio (MVP)
   - Objective: Minimize portfolio variance: $min_w \;\; w^T \sum w + \alpha ||w - w_0||^2$ subject to : $\sum_i w_i = 1, w_i \geq 0$ where Σ is the covarinace matrix of return, w is the the portfolio weight vector, and w_0 is the original allocation derived from 2024 AUM. The regulaization term $\alpha||w - w_0||^2$ penalizes deviation from from this assest-based baseline.

b. Maximum Sharp Ratio (MSR)
   - Objective: Maximize the Sharp Ratio: $max_w \;\; \frac{w^T \mu - r_f}{\sqrt{w^T \sum w}} - \alpha||w - w_0||^2$ subject to the same constraints as MVP. where μ is the expected return vector, and r_f is the risk-free rate (assumed to be 2%). Again, w_0 anchors the optimization to observed asset structures.

c. Risk Parity (RP)
   - Objective: Allocate equal risk contribution: $w_i \propto \frac{1}{\alpha_i}$ where α_i is the standard deviation of assets i. The weights are then normailized to sum to One.

d. Conditional Value-at-Risk (CVaR)
   - Objective: Minimize expected loss in the worst α% of outcomes : $min_w \;\; CVaR_\alpha(w) + \alpha||w - w_0||^2$ where $CVaR_\alpha(w) = -\mathbb{E}[R_p \leq VAR_\alpha]$. The portfolio returns R_p are calculated as $R_p = Xw$ where X is the return matrix, and w_0 serves as the reference allocation based on the actual assets distribution.

Portfolio Evaluation. For each model, optimal weights were computed and applied to the log return matrix. In addition, performance metrics including annualized return, volatility, Sharpe Ratio, and maximum drawdown were calculated.

4. Empirical Results and Analysis

Tables 2-4 and Figures 1-3 present the empirical results of portfolio optimization. Specifically, the results reveal substantial differences in both allocation structure and performance outcomes depending on the selected strategy. MVP, MSR, RP and CvaR models were compared across several key performance metrics.

Table 2 presents the asset allocation outcomes derived from four optimization frameworks—MVP, MSR, RP, and CVaR—applied to SWFs over the 2011–2024 period. The allocation patterns reveal substantial differences in concentration, diversification, and strategic orientation across models.

The MVP model generates relatively diversified portfolios, with meaningful allocations across a broad set of SWFs. Notably, China Investment Corporation (18.2%), Norway Government Pension Fund Global (15.4%), and Abu Dhabi Investment Authority (13.1%) receive the highest weights. The inclusion of smaller funds such as the Ireland Strategic Investment Fund and Solidium, albeit at low levels, underscores the model's conservative orientation, as it seeks to minimize total portfolio variance irrespective of individual asset performance.

In contrast, the MSR optimization exhibits a pronounced concentration toward high-return, low-volatility funds, most notably Temasek Holdings (20.8%), Abu Dhabi Investment Authority (15.7%), and China Investment Corporation (14.7%). Many funds—including large institutions such as Norway and Alaska—receive near-zero weights, indicating that the MSR model heavily prioritizes historical Sharpe ratios over diversification. This return-centric allocation profile offers superior expected performance but at the cost of exposure concentration and potential risk amplification.

The Risk Parity strategy yields the most evenly distributed portfolio, reflecting its design principle of equalizing marginal risk contributions. Alberta Investment Management Corporation (8.6%), Temasek Holdings (7.7%), and the Hong Kong Monetary Authority Investment Portfolio (7.0%) receive the largest allocations, yet even the least-weighted funds maintain non-negligible positions. This distribution underscores the RP model's capacity to promote structural balance and robustness, making it suitable for SWFs with mandates emphasizing diversification and long-term stability.

The CVaR optimization, which targets downside risk minimization, results in allocations that, while more concentrated than MVP or RP, are slightly more balanced than those under MSR. Dominant positions are held by Norway (25.1%), China (20.2%), and Abu Dhabi (15.2%). The allocation structure reflects a preference for funds with both strong historical performance and lower tail-risk exposure. However, the pronounced weight skew suggests vulnerability to idiosyncratic or geopolitical shocks concentrated in a few sovereign entities.

Overall, the allocation outcomes across models reflect their theoretical underpinnings and optimization priorities. MVP emphasizes risk dispersion, MSR maximizes expected return per unit of risk, RP equalizes systemic risk contributions, and CVaR focuses on mitigating extreme losses. From a policy perspective, these results highlight the importance of aligning optimization methodologies with each SWF's strategic mandate, risk appetite, and governance framework. Furthermore, the allocation concentration observed in MSR and CVaR models may necessitate the introduction of diversification constraints or rebalancing thresholds to manage systemic and concentration risks in practice.

Figure 1 visually compares the portfolio weights assigned to the top 10 SWFs across all four strategies. Both MSR and CVaR emphasize high-return, low-volatility funds—particularly China, Norway, and Abu Dhabi—while MVP and RP adopt more balanced weighting. This highlights the strategic trade-off between return-seeking and diversification. The RP model's moderate allocations across most funds underscore its design to equalize risk contributions, whereas CVaR's large exposures reflect a focus on tail-risk-adjusted return.

Figure 2 shows that the CVaR and MSR strategies achieved the highest cumulative returns from 2011 to 2024, indicating strong long-term performance. The CVaR outperformed slightly, balancing downside risk with growth. MVP delivered stable but lower returns, reflecting its conservative risk profile. RP trailed all others, highlighting its focus on risk balance over return maximization. These results emphasize the trade-off between return, risk, and diversification across models.

Table 3 and Figure 3 collectively compare the performance of the four optimization strategies—Minimum Variance Portfolio (MVP), Maximum Sharpe Ratio (MSR), Risk Parity (RP), and Conditional Value-at-Risk (CVaR)—using key metrics: annualized return, volatility, Sharpe ratio, and maximum drawdown.

The MSR model exhibits the strongest risk-adjusted performance, achieving the highest Sharpe ratio (3.01) and the lowest volatility (1.54%). Despite not having the highest absolute return, its ability to deliver consistent returns per unit of risk positions as the most efficient strategy.

The CVaR strategy delivers the highest annualized return (7.78%) but with increased volatility (4.12%). This trade-off reflects its design emphasis on limiting downside risk while still capturing market upside. The resulting Sharpe ratio (1.40) is competitive, indicating that CVaR effectively balances risk and return for funds with higher tolerance for volatility.

In contrast, the MVP model achieves the lowest volatility (2.24%) and a solid Sharpe ratio (1.85), reinforcing its role in capital preservation mandates. Although it sacrifices some return (6.15%), it offers stability and protection against large drawdowns.

The RP strategy underperforms on all core metrics, with the lowest return (5.49%) and Sharpe ratio (0.95). While RP's emphasis on equal risk contribution supports diversification, it appears less effective in optimizing portfolio growth or risk efficiency over the study period.

Overall, the combined evidence from Table 3 and Figure 3 underscores the strategic distinctions among the models. MSR and CVaR are preferable for performance-focused mandates, while MVP is ideal for low-risk objectives. RP, though less performant, may still appeal to institutions prioritizing risk balance and broad diversification.

Collectively, the results suggest that model selection significantly influences not just expected return, but the profile of portfolio risk and allocation concentration. These insights emphasize the importance of aligning optimization techniques with the fund's institutional mandate, risk tolerance, and investment constraints.

5. Conclusion

These findings underscore the importance of optimization objective alignment with fund mandates. For example, MSR and CVaR may be more suitable for SWFs with aggressive return targets and the capacity to tolerate risk. On the other hand, MVP may align with funds prioritizing capital preservation and stability. Risk Parity, though less performant in absolute returns, offers diversification benefits and may appeal to conservative allocators.

The dominance of a few SWFs in optimized portfolios across all models suggests structural advantages (e.g., size, historical performance, asset diversification). This raises questions about concentration risk, particularly under CVaR and MSR strategies, which may be mitigated by introducing allocation constraints or diversification limits in practice.

The analysis confirms that portfolio optimization can significantly affect SWF performance outcomes depending on the selected model. While MSR delivers superior risk-adjusted returns, CVaR provides competitive performance with a focus on downside risk. MVP serves risk-averse strategies, and RP offers diversification advantage. Future research may explore the impact of dynamic rebalancing, inclusion of illiquid assets, or the application of multi-objective optimization frameworks to align better with heterogeneous SWF goals.

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Table 1: Information about SWF

SWF	Fund Type	Primary Industry / Funding Source	Country
Norway Government Pension Fund Global	Pension / Savings Fund	Oil & Gas (Petroleum Revenues)	Norway
China Investment Corporation	Stabilization & Strategic Investment Fund	Foreign Exchange Reserves	China
Abu Dhabi Investment Authority	Savings / Intergenerational Fund	Oil & Gas	United Arab Emirates
Public Investment Fund	Strategic Development Fund	Oil & Gas (historically), Economic Diversification	Saudi Arabia
Hong Kong Monetary Authority Investment Portfolio	Reserve Investment Fund	Foreign Exchange Reserves	Hong Kong (China)
Temasek Holdings	Strategic Investment / Development Fund	State-Owned Enterprises & Fiscal Surpluses	Singapore
Korea Investment Corporation	Stabilization / Savings Fund	Foreign Exchange Reserves	South Korea
National Welfare Fund	Pension / Stabilization Fund	Oil & Gas	Russia
Alberta Investment Management Corporation	Pension & Endowment Manager	Oil & Gas Royalties & Public Pensions	Canada
Alaska Permanent Fund Corporation	Savings / Intergenerational Fund	Oil & Gas	United States
University of Texas Investment Management Company	Endowment Fund	Oil & Gas (Permanent University Fund)	United States
New Mexico State Investment Council	Pension & Trust Fund	Oil & Gas & Mineral Revenues	United States
New Zealand Superannuation Fund	Pension / Savings Fund	Fiscal Surpluses	New Zealand
Khazanah Nasional	Strategic Development Fund	State-Owned Enterprises	Malaysia

Wyoming State Loan and Investment Board	Permanent Trust Fund	Oil, Gas & Mineral Revenues	United States
Mumtalakat Holding	Strategic Investment / Holding Fund	State-Owned Enterprises	Bahrain
Ireland Strategic Investment Fund	Strategic Development Fund	Fiscal Surpluses	Ireland
Solidium	Strategic Domestic Equity Fund	State-Owned Equity Holdings	Finland
Social and Economic Stabilization Fund	Stabilization Fund	Copper & Commodity Revenues	Chile
Alabama Trust Fund	Permanent Trust Fund	Oil, Gas & Mineral Royalties	United States
Oklahoma Tobacco Settlement Endowment Trust	Endowment / Stabilization Fund	Tobacco Settlement Revenues	United States

Table 2: Annualized Return and Volatility by SWF

SWF	Annualized Return	Annualized Volatility
Norway Government Pension Fund Global	0.0877	0.0991
China Investment Corporation	0.0878	0.0739
Abu Dhabi Investment Authority	0.0404	0.1300
Public Investment Fund	0.1266	0.1841
Hong Kong Monetary Authority Investment Portfolio	0.0336	0.0637
Temasek Holdings	0.0628	0.0580
Korea Investment Corporation	0.1228	0.1348
National Welfare Fund	-0.0107	0.1301
Alberta Investment Management Corporation	0.0433	0.0519
Alaska Permanent Fund Corporation	0.0646	0.0824
University of Texas Investment Management Company	0.0982	0.0980
New Mexico State Investment Council	0.0692	0.0925
New Zealand Superannuation Fund	0.0986	0.1275
Khazanah Nasional	0.0364	0.1172
Wyoming State Loan and Investment Board	0.0491	0.0483
Mumtalakat Holding	0.0362	0.1118
Ireland Strategic Investment Fund	-0.0111	0.1097
Solidium	0.0027	0.2793
Social and Economic Stabilization Fund	-0.0916	0.5000
Alabama Trust Fund	0.0106	0.0775
Oklahoma Tobacco Settlement Endowment Trust	0.0883	0.0821

Table 3: Optimized Portfolio Weights

SWF	MVP	MSR	RP	CVaR
Norway Government Pension Fund Global	0.1535	0.0001	0.0452	0.2505
China Investment Corporation	0.1821	0.1466	0.0607	0.2018
Abu Dhabi Investment Authority	0.1308	0.1573	0.0345	0.1523
Public Investment Fund	0.0981	0.0760	0.0244	0.1357
Hong Kong Monetary Authority Investment Portfolio	0.0576	0.0001	0.0703	0.0754
Temasek Holdings	0.1073	0.2081	0.0774	0.0707
Korea Investment Corporation	0.0056	0.1179	0.0333	0.0298
National Welfare Fund	0.0001	0.0001	0.0345	0.0114
Alberta Investment Management Corporation	0.0428	0.0790	0.0864	0.0184
Alaska Permanent Fund Corporation	0.0151	0.0001	0.0544	0.0123
University of Texas Investment Management Company	0.0001	0.0098	0.0457	0.0111
New Mexico State Investment Council	0.0444	0.0896	0.0485	0.0062
New Zealand Superannuation Fund	0.0001	0.0001	0.0352	0.0069
Khazanah Nasional	0.0635	0.0764	0.0383	0.0058
Wyoming State Loan and Investment Board	0.0001	0.0001	0.0929	0.0039
Mumtalakat Holding	0.0001	0.0001	0.0401	0.0025
Ireland Strategic Investment Fund	0.0540	0.0001	0.0409	0.0030
Solidium	0.0001	0.0001	0.0160	0.0011
Social and Economic Stabilization Fund	0.0307	0.0382	0.0090	0.0005
Alabama Trust Fund	0.0137	0.0001	0.0579	0.0006
Oklahoma Tobacco Settlement Endowment Trust	0.0001	0.0001	0.0546	0.0003

Table 4: Performance Metrics Across Optimization Models

Metric	MVP	MSR	RP	CVaR
Annualized Return(%)	6.15	6.63	5.49	7.78
Annualized Volatility(%)	2.24	1.54	3.68	4.12
Sharpe Ratio	1.85	3.01	0.95	1.40
Max Drawdown (%)	2.00	3.00	-0.50	1.40

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Figure 1: Optimal Allocations (Top 10 SWFs)

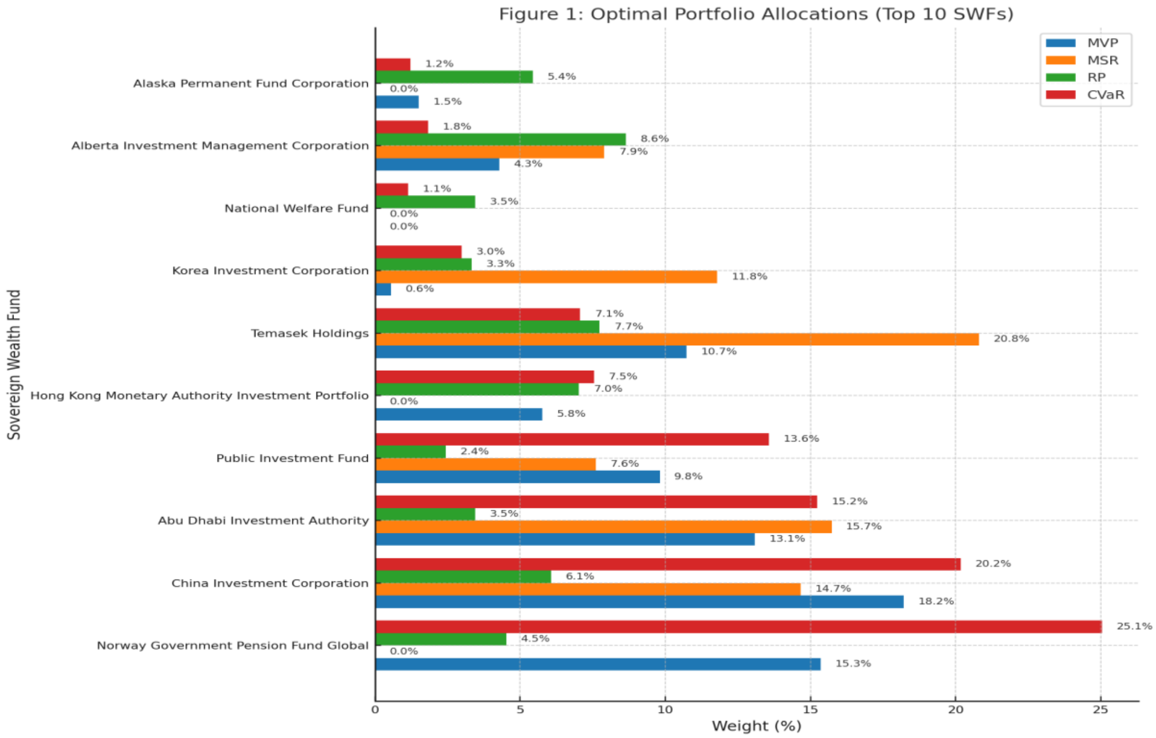

Figure 2: Cumulative Portfolio Returns

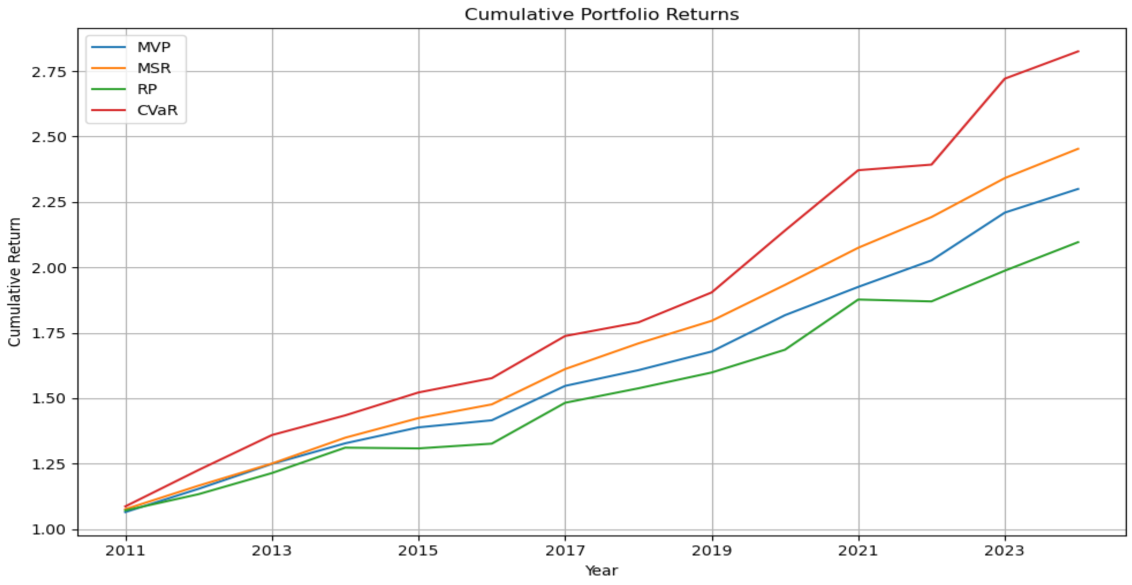

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Figure 3: Performance Metrics Comparison