NOVA IMS Information Management School

Enhancing portfolio optimization with machine learning methods: A comparative study using commodity markets data

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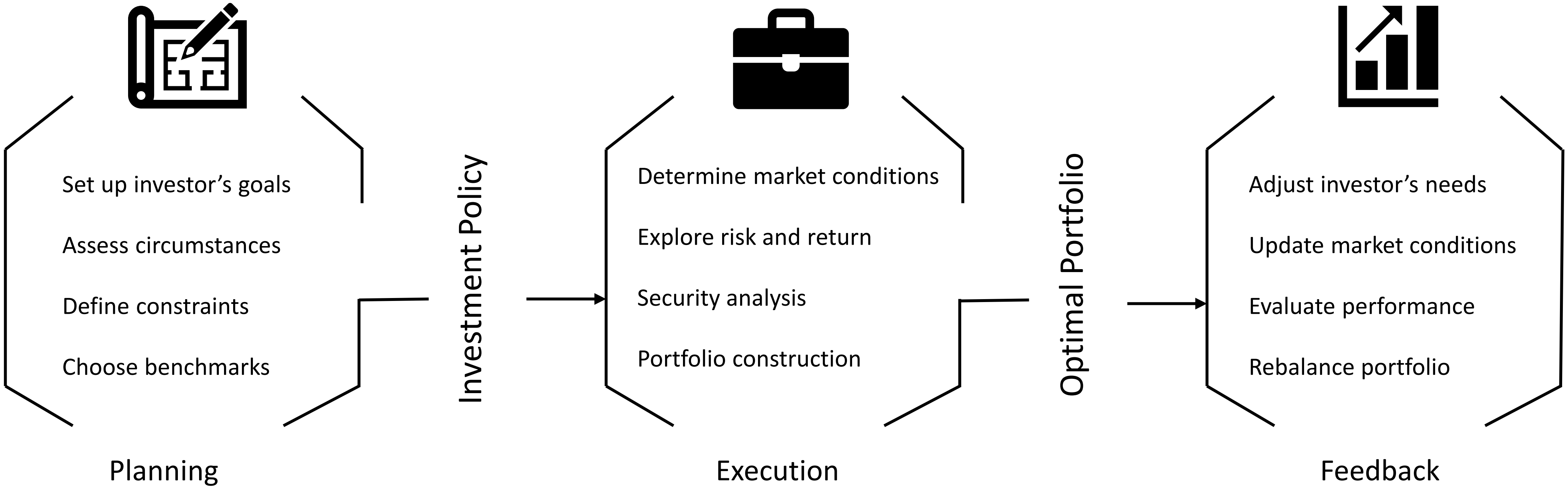
Portfolio Management Process



1 Introduction

A momentary overview

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Portfolio Theory Evolution

Modern Portfolio Theory

- Introduced by Markowitz in the 1950s
- It focuses on mean-variance optimization to build portfolios that maximize returns for a given level of risk or minimize risk for a given level of return
- **Key Concepts:** Diversification, efficient frontier, risk-return trade-off

Continuous Time Finance

- Extends modern portfolio theory to a continuous-time setting, allowing for dynamic rebalancing and more sophisticated modeling of financial markets
- **Key Concepts:** Black-Scholes-Merton option pricing model Merton's portfolio problem

Robust Optimization

- Addresses the limitations of mean-variance optimization by incorporating uncertainty and variability in model parameters
- Focuses on creating portfolios that are resilient to model errors and adverse market conditions
- **Key Concepts:** Uncertainty sets, worst-case scenarios, stress testing

Risk Based Approaches

- Emphasizes managing and minimizing risk rather than focusing solely on expected returns
- Examples include risk parity, maximum diversification and minimum variance portfolios
- **Key Concepts:** Tail risk management risk budgeting, volatility targeting

Machine Learning

- Applies advanced algorithms and computational techniques to analyze and optimize portfolios
- Handles large datasets, enhances prediction accuracy and automates decision-making processes
- **Key Concepts:** Support vector machines, neural networks, reinforcement learning

1 Introduction

Different strategies provide different methodologies

- Different strategies have unique input requirements, selecting the right one depends on investors preferences. Here, we evaluate how these strategies perform across various scenarios, shifting the focus from simply building portfolios to understanding how each strategy adapts and performs under different conditions

Strategy	Group	Expected Outcome
Mean Variance Optimization	Return Risk Tradeoff	• Optimal portfolio that balances risk and return • Efficient Frontier (set of portfolios with maximum return for a given level of risk)
Global Minimum Variance	Risk Based Allocation	• Portfolio with the lowest possible risk (variance) • Suitable for risk-averse investors seeking minimal volatility
Maximum Diversification	Diversification Based	• Portfolio that maximizes diversification • Improved risk-adjusted returns by spreading risk across assets
Risk Parity	Risk Based Allocation	• Portfolio where each asset or risk factor contributes equally to overall risk • Balanced risk distribution across assets or factors
Hierarchical Risk Parity	Risk Based Allocation	• Portfolio with hierarchical clustering of assets • Reduced risk concentration through clustering and hierarchical risk allocation
Equal Weights	Diversification Based	• Simple and equally weighted portfolio • Provides straightforward diversification with equal exposure to each asset

Research Question 01	How do different portfolio optimization strategies perform in terms of risk-adjusted returns under different portfolio allocations?
Research Question 02	How does the inclusion of short selling impact the performance of different portfolio optimization strategies?
Research Question 03	How does the performance of portfolios optimized with various strategies compare to an equal-weighted benchmark portfolio, particularly when considering short selling as a constraint?

2 Research Methodology

1. Comparison of different strategies

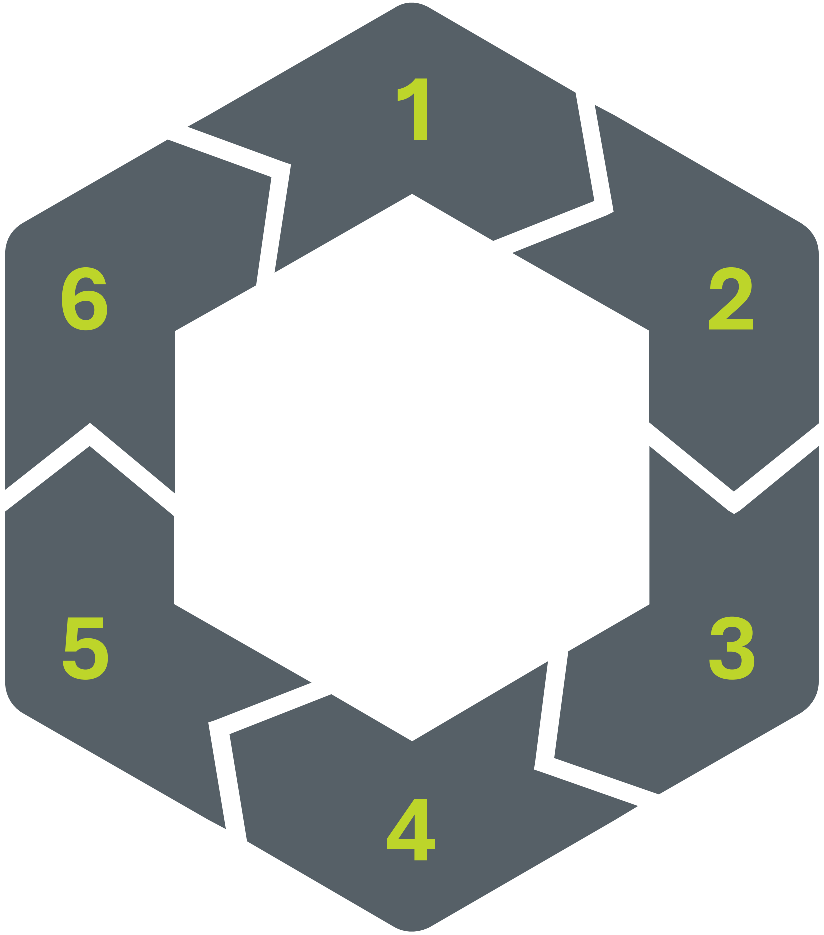
- Detailed analysis of various portfolio optimization methods, including traditional approaches and advanced machine learning techniques.
- Data ranges from **2010** until **2023**
- Time horizon for **three, five** and **seven years**

2. Focus on commodities

- Our paper utilizes data from **seven different commodity groups**, addressing a gap in the literature predominantly focused on equity markets

3. Short selling and benchmark

- Inclusion of **short selling as a constraint** in the optimization procedure
- **Equally weighted portfolio** used as a benchmark



4. Portfolio simulations

- A total of **one hundred** different portfolio allocations were performed
- Metrics such as Sharpe Sortino and Downside Deviation computed for each simulation

5. Rebalancing approach

- Portfolios are **rebalanced semi-annually** to reflect changes in market conditions and maintain optimal asset allocation

6. Final assessment

- **Median of portfolio simulations** considered to minimize the impact of outliers, ensuring reliable performance assessment.

Research Methodology

Commodity universe

Commodity Group	Commodities
Energy	WTI Crude Oil, Gasoline, Natural Gas, Heating Oil, Brent Crude Oil
Precious Metals	Gold, Silver, Platinum, Palladium
Base Metals	Zinc, Copper
Agriculture	Wheat, Corn, Soybeans, Cocoa, Rice, Oats, Milk, Dry Whey, Butter, Non-Fat Dry Milk
Livestock	Lean Hogs, Live Cattle, Feeder Cattle
Softs	Sugar, Coffee, Cotton
ETFs	Invesco DB Base Metals Fund, United States Oil Fund LP, Invesco DB Agriculture Fund, Invesco DB Commodity Index Tracking Fund, iShares S&P GSCI Commodity-Indexed Trust, Elements Rogers International Commodity Index-Total Return ETN

2 Research Methodology

Optimization Problem

Strategy	Optimization Objective	Constraints
Mean Variance Optimization	$minimize_w \ w^T \Sigma w$	$w^T\mu \geq \beta$ (budget) $\sum_{i=1}^{N} w_i = 1$ (Weights add to 1) $w_i > 0, \forall_i$ (no short selling)
Global Minimum Variance	$minimize_w \ w^T \Sigma w$	$\sum_{i=1}^{N} w_i = 1$ (Weights add to 1) $w_i > 0, \forall_i$ (no short selling)
Maximum Diversification	$maximize \ \frac{\sum_{i=1}^{N} w_i \sigma_i}{\sqrt{w^T \Sigma w}}$	$\sum_{i=1}^{N} w_i = 1$ (Weights add to 1) $w_i > 0, \forall_i$ (no short selling)
Risk Parity	$\min_w \sum_{i=1}^{N} \left(RC_i - \frac{\sigma_p}{N} \right)^2$	$\sum_{i=1}^{N} w_i = 1$ (Weights add to 1) $w_i > 0, \forall_i$ (no short selling)
Hierarchical Risk Parity	$\mathrm{Cluster} = \mathrm{Tree\ Clustering}(\rho)$ $\Sigma^{\mathrm{QD}} = \mathrm{Reorder}(\Sigma, \mathrm{Cluster})$ $\mathrm{w_i} = \mathrm{Allocate\ Risk\ Parity}\ (\Sigma^{\mathrm{QD}}, \mathrm{Cluster})$	$\sum_{i=1}^{N} w_i = 1$ (Weights add to 1) $w_i > 0, \forall_i$ (no short selling)
Equal Weights	$w_i = \frac{1}{N}, for\ all\ asset\ i$	No constraints (equal allocation)

Legend:

w: Weight vector

∑: Covariance matrix

μ: Expected returns

σ_i: Volatility of assset i

N: Number of assets

RC: Risk contribution

ρ: Correlation matrix

3

Results

Annualized results with no short selling for three, five and seven-year windows

A. Three-year investment period								
Strategy	**Returns**	**Volatility**	**Sharpe**	**Max Drawdown**	**Sortino**	**Downside Deviation**	**VAR**	**CVAR**
MVO	0.1409	0.1359	1.0078	-0.1506	1.7093	0.0057	0.0129	0.0005
GMV	0.1039	0.1005	0.9655	-0.1518	1.5287	0.0044	0.0099	0.0003
MD	0.1094	0.1169	0.8646	-0.1883	1.3777	0.0051	0.0115	0.0004
RP	0.1253	0.1594	0.7673	-0.2255	1.2272	0.0071	0.0161	0.0005
HRP	0.1528	0.1600	0.9082	-0.3246	1.1380	0.0093	0.0209	0.0007
EW	0.1267	0.1490	0.8457	-0.2351	1.3612	0.0066	0.0156	0.0004

B. Five-year investment period								
Strategy	**Returns**	**Volatility**	**Sharpe**	**Max Drawdown**	**Sortino**	**Downside Deviation**	**VAR**	**CVAR**
MVO	0.1094	0.1350	0.8155	-0.2215	1.3404	0.0059	0.0134	0.0005
GMV	0.0851	0.1050	0.7917	-0.1914	1.2782	0.0046	0.0100	0.0004
MD	0.0934	0.1209	0.7319	-0.2243	1.2162	0.0053	0.0112	0.0005
RP	0.1038	0.1599	0.6573	-0.3064	1.0408	0.0073	0.0155	0.0007
HRP	0.1123	0.1678	0.7036	-0.4206	0.8689	0.0104	0.0202	0.0011
EW	0.1027	0.1509	0.7205	-0.2966	1.1302	0.0068	0.0148	0.0006

C. Seven-year investment period								
Strategy	**Returns**	**Volatility**	**Sharpe**	**Max Drawdown**	**Sortino**	**Downside Deviation**	**VAR**	**CVAR**
MVO	0.0876	0.1180	0.7608	-0.2457	1.2202	0.0052	0.0112	0.0005
GMV	0.0645	0.0983	0.6220	-0.1941	0.9954	0.0043	0.0092	0.0005
MD	0.0775	0.1130	0.6599	-0.2253	1.0728	0.0049	0.0105	0.0005
RP	0.0752	0.1465	0.5206	-0.3152	0.8205	0.0066	0.0139	0.0007
HRP	0.0882	0.1614	0.5744	-0.4405	0.7705	0.0093	0.0185	0.0010
EW	0.0804	0.1392	0.6095	-0.2991	0.9633	0.0062	0.0135	0.0007

Legend:

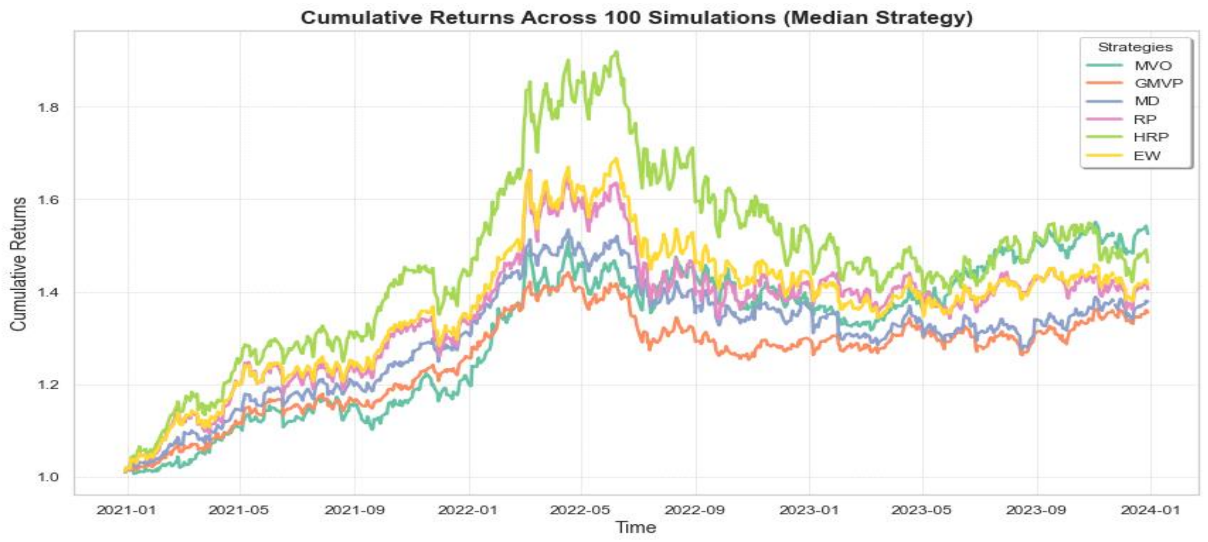
Best performers

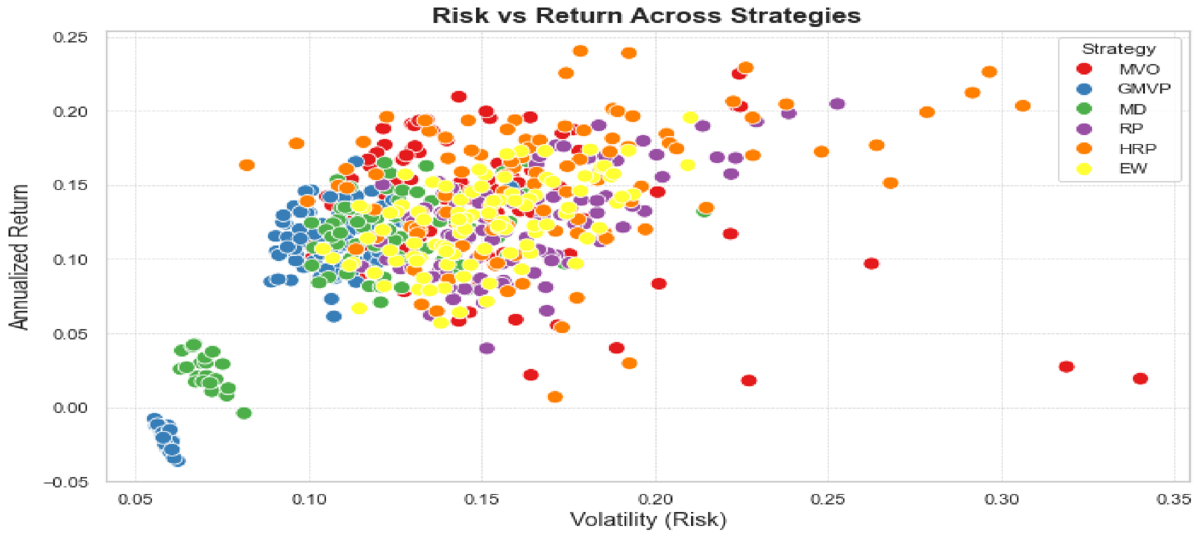
Middle performers

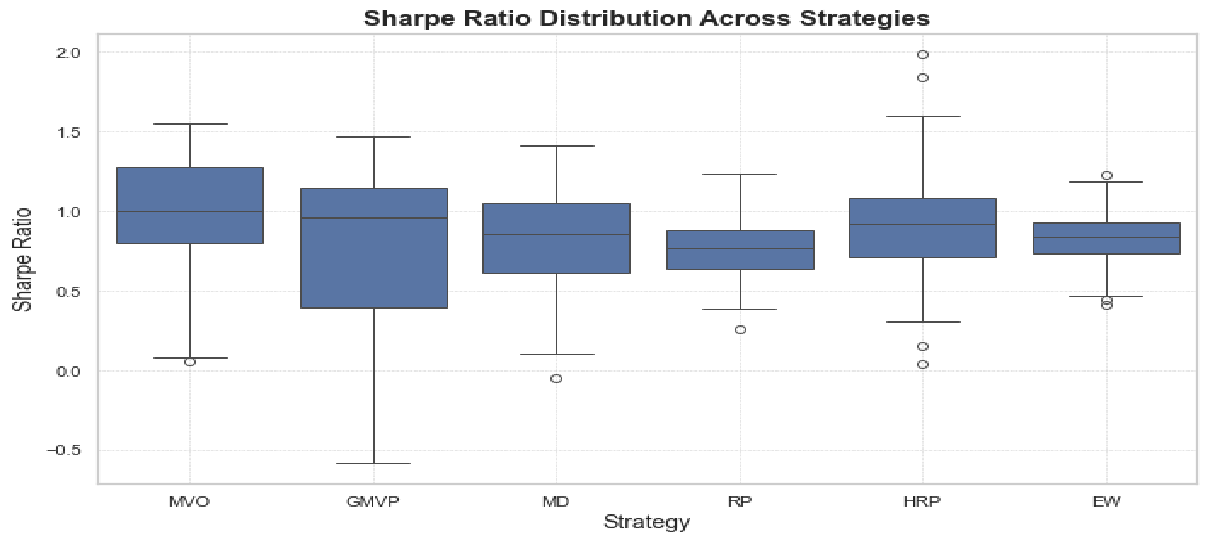
Worst performers

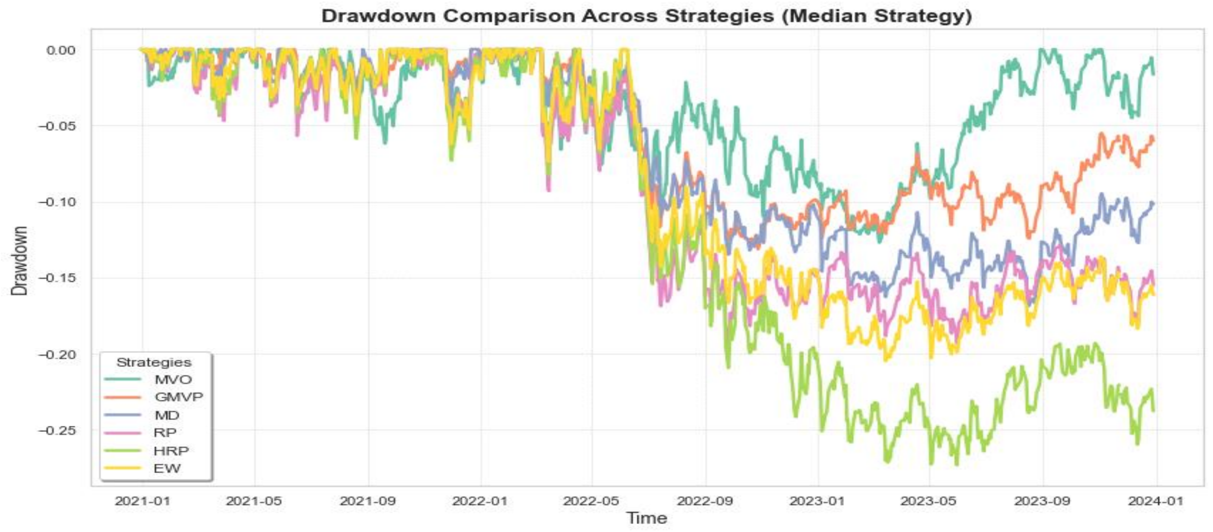
3 Results

Visual Representation: three-year approach









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Results

Annualized results with short selling for three, five and seven-year windows

A. Three-year investment period

Strategy	Returns	Volatility	Sharpe	Max Drawdown	Sortino	Downside Deviation	VAR	CVAR
MVO	0.1373	0.2287	0.5079	-0.2640	0.8603	0.0098	0.0224	0.0012
GMV	0.1071	0.0975	0.9829	-0.1511	1.5901	0.0042	0.0097	0.0003
MD	0.1049	0.1204	0.7424	-0.1989	1.2095	0.0054	0.0121	0.0004
RP	0.1300	0.1650	0.7767	-0.2270	1.2551	0.0074	0.0162	0.0005
HRP	0.1089	0.1687	0.6007	-0.1549	1.4457	0.0049	0.0111	0.0004
EW	0.1267	0.1490	0.8457	-0.2351	1.3612	0.0066	0.0156	0.0004

B. Five-year investment period

Strategy	Returns	Volatility	Sharpe	Max Drawdown	Sortino	Downside Deviation	VAR	CVAR
MVO	0.1749	0.2314	0.7444	-0.2989	1.3134	0.0093	0.0203	0.0011
GMV	0.0843	0.1014	0.8422	-0.1940	1.3650	0.0044	0.0096	0.0004
MD	0.0926	0.1253	0.7007	-0.2357	1.1460	0.0056	0.0119	0.0005
RP	0.1061	0.1647	0.6573	-0.3165	1.0464	0.0075	0.0156	0.0007
HRP	0.0931	0.1785	0.4951	-0.2040	1.2499	0.0050	0.0110	0.0004
EW	0.1027	0.1509	0.7205	-0.2966	1.1302	0.0068	0.0148	0.0006

C. Seven-year investment period

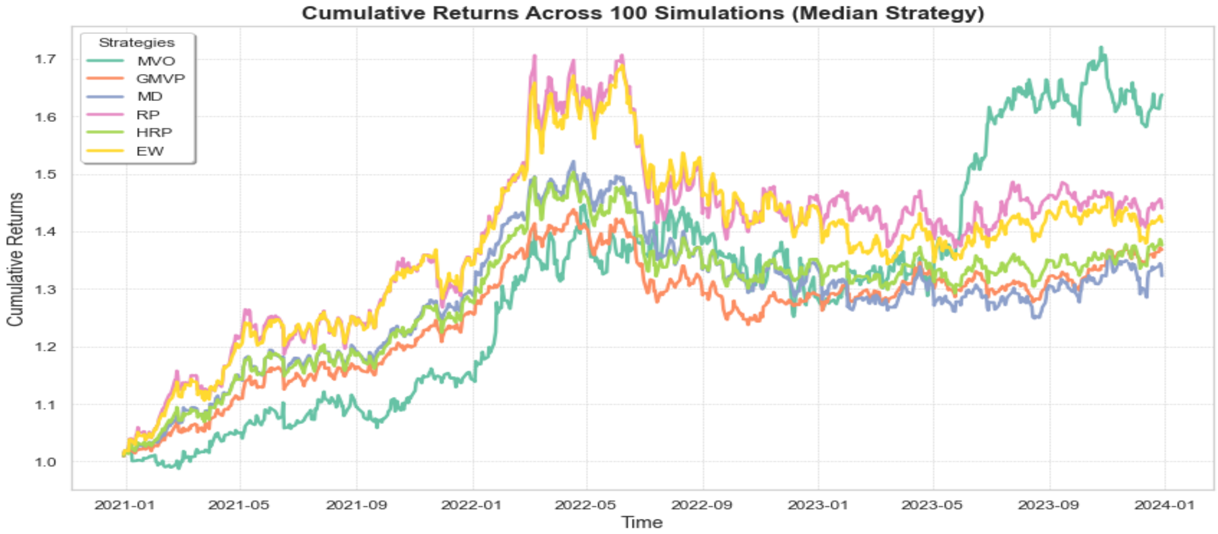
Strategy	Returns	Volatility	Sharpe	Max Drawdown	Sortino	Downside Deviation	VAR	CVAR
MVO	0.1273	0.1456	0.8550	-0.2787	1.4443	0.0063	0.0133	0.0007
GMV	0.0637	0.0958	0.6398	-0.1988	1.0256	0.0042	0.0089	0.0005
MD	0.0787	0.1171	0.6561	-0.2363	1.0663	0.0052	0.0107	0.0006
RP	0.0768	0.1486	0.5212	-0.3254	0.8207	0.0068	0.0141	0.0007
HRP	0.0715	0.1587	0.4119	-0.2045	1.0147	0.0046	0.0098	0.0005
EW	0.0804	0.1392	0.6095	-0.2991	0.9633	0.0062	0.0135	0.0007

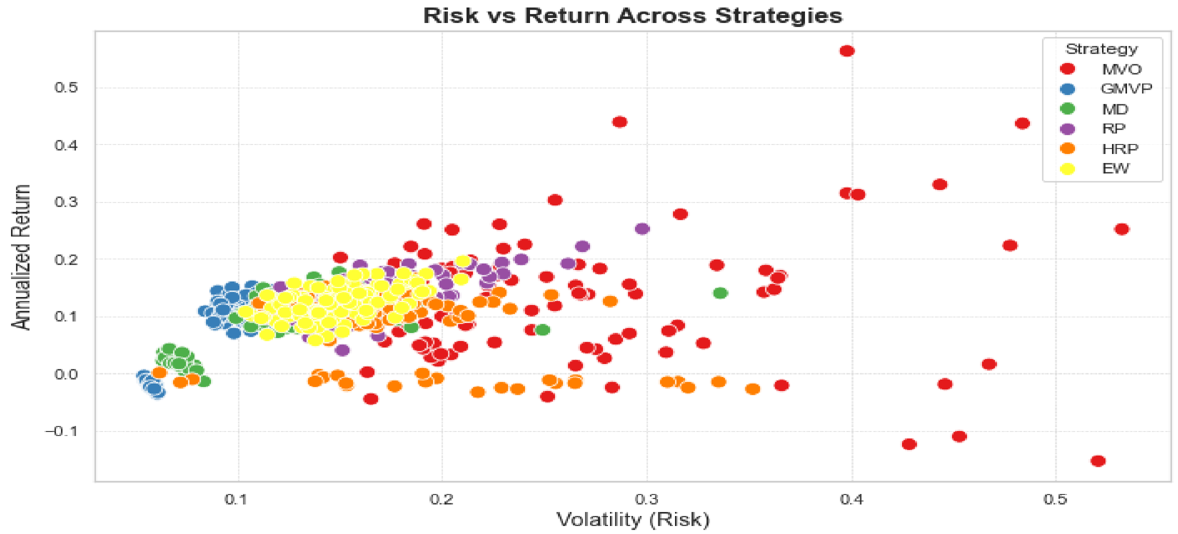
Legend:

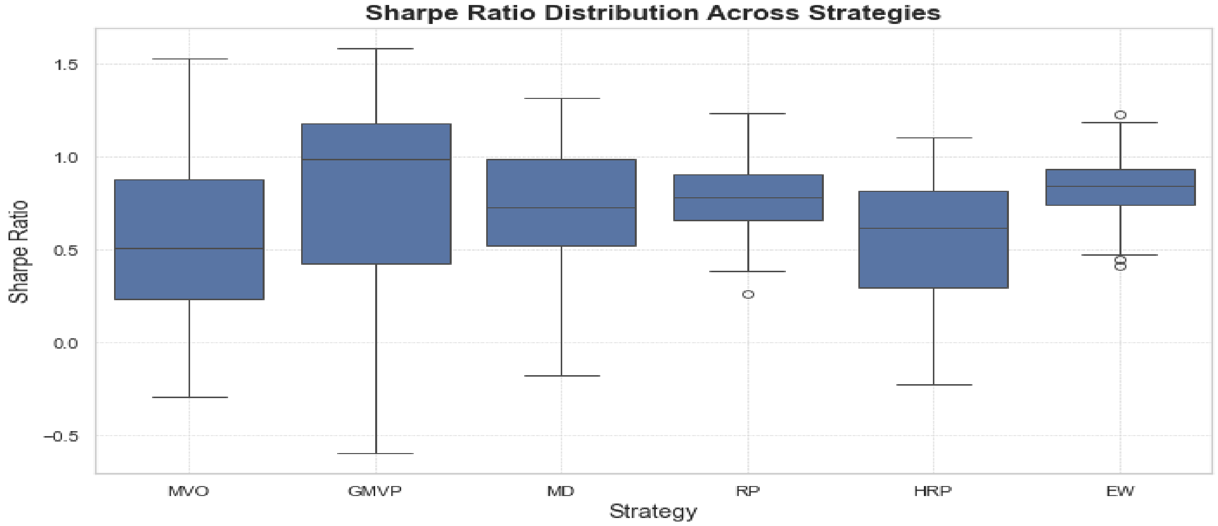
- Best performers
- Middle performers
- Worst performers

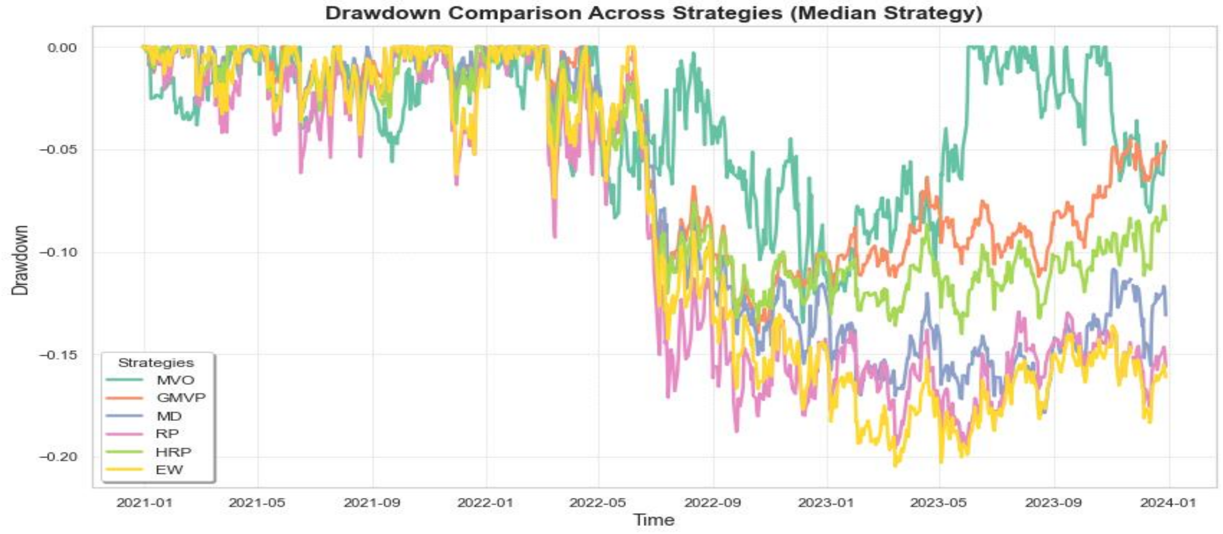
3 Results

Visual Representation: three-year approach









Final Conclusions

Main Findings

1. **Conclusion #1**

   Strategies involving short selling can boost returns but increase risk and volatility, requiring risk assessments and alignment with specific investment goals;

2. **Conclusion #2**

   GMV offers stability with lower volatility and drawdowns, while MVO provides higher returns but with greater risks. MD balances performance with increased risk under short selling. Diversifying strategies can help mitigate risks and enhance overall gains.

3. **Conclusion #3**

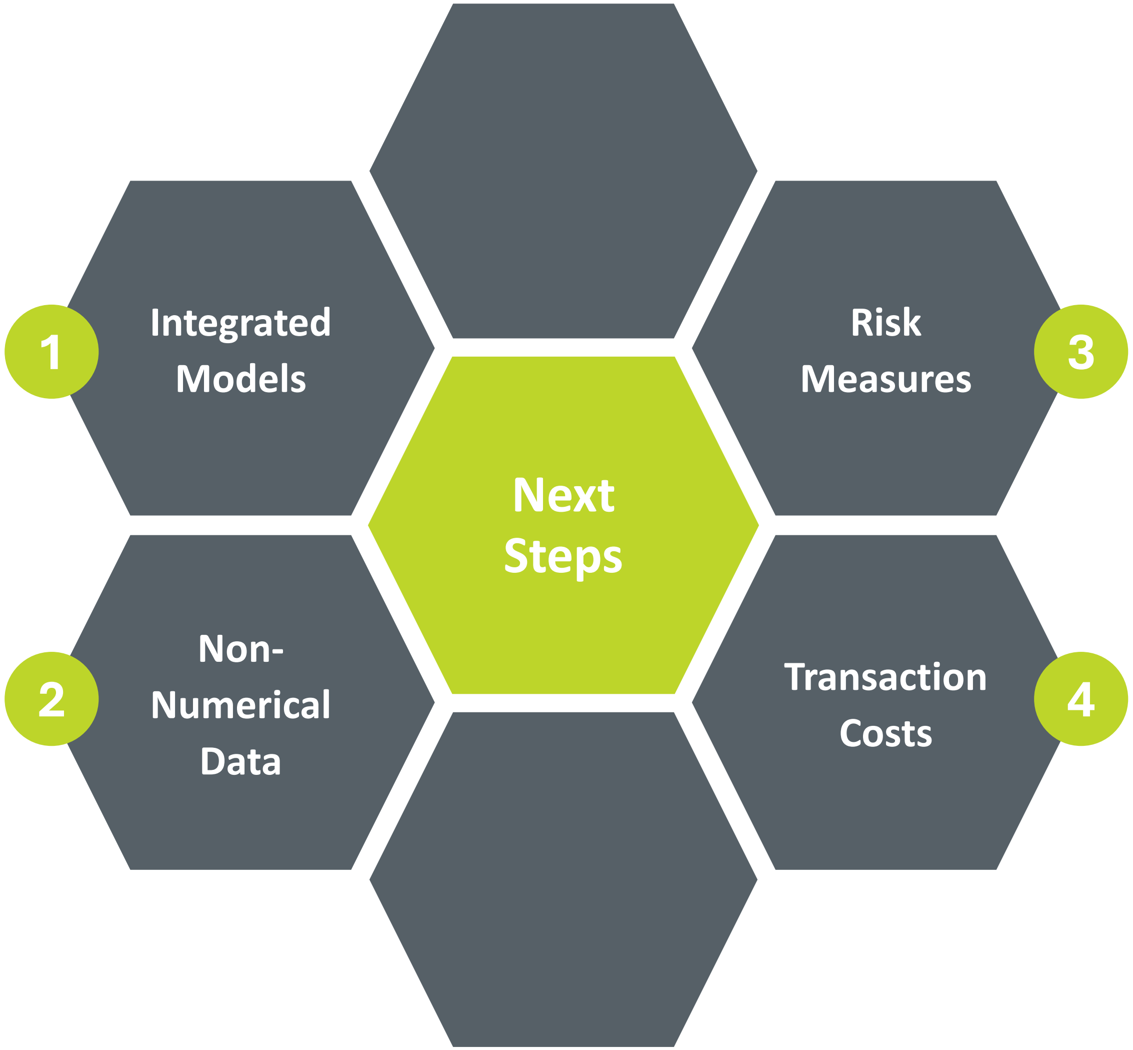
   RP and HRP strategies show balanced risk allocation but higher volatility and drawdown risks with short selling. Continuous adjustment of asset weights, robust risk management tools, and scenario analysis are crucial for maintaining stability;

4. **Conclusion #4**

   The EW strategy, being simple and transparent, competes effectively with complex strategies, avoiding over-optimization pitfalls and providing a practical, easy-to-manage investment method.

5 Final Conclusions

Recommendations for future work



1) Integrated Models

Expand portfolio optimization models to incorporate a broader range of criteria, including economic, social, and environmental factors.

2) Non-Numerical Data

Develop tools to convert qualitative information, such as investor sentiment from textual data, into numerical inputs for optimization, enhancing the ability to tackle a wider range of portfolio problems

3) Risk Measures

Explore different objective functions using alternative risk measures like Value at Risk (VaR), Conditional Value at Risk (CVaR), or drawdown, providing a more comprehensive assessment in risk-based strategies

4) Transaction Costs

Model transaction costs, including direct and indirect to better assess strategy performance, especially in commodity markets.

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Thank You!

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