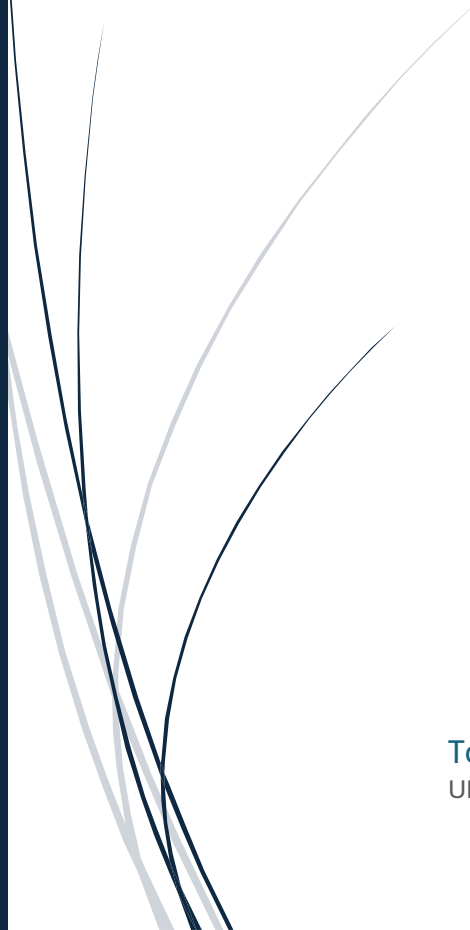


2024-2025

Investment Strategies

Adaptive Asset Allocation



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Introduction

This study analyzes a set of asset allocation strategies that combine various position sizing rules with the main risk-based and optimization approaches. The work draws practical insights from two key papers: “Adaptive Asset Allocation: A Primer” and “Risk-Parity versus Mean-Variance.” The first highlights the limitations of the traditional application of Modern Portfolio Theory when used in a purely strategic framework, and proposes an “adaptive” approach in which risk/return parameters are estimated over shorter rolling windows and dynamically updated through time. The operational path begins with an equally weighted (EW) portfolio, to which momentum-based rules and risk-driven weighting schemes are progressively added, with the objective of improving risk-adjusted performance relative to a static allocation. The second contribution compares, on both theoretical and empirical grounds, the Risk Parity and Mean-Variance allocation frameworks, clarifying when the two logics tend to converge (e.g., in Volatility Parity contexts) and discussing their implications in terms of performance, drawdown, and robustness.

Our goal is to systematically explore different strategies and their combinations, comparing them with one another and with a monthly rebalanced equally weighted benchmark. Specifically:

1. We evaluate individually EW, Momentum, Risk Parity, Volatility Parity, Minimum-Variance, and Mean-Variance strategies;
2. We construct hybrid combinations that integrate momentum-based selection and weighting with risk-based allocation criteria;
3. We measure whether (and to what extent) the progressive integration of these techniques yields an overall improvement in the risk/return profile.

The analysis is conducted using daily logarithmic returns and monthly rebalancing, with volatility and correlation inputs estimated on a daily basis to enhance informational precision. Performance evaluation is carried out through a set of standard metrics (CAGR, volatility, Sharpe, Sortino, drawdown, and Calmar ratios) as well as through a proprietary composite indicator (Omega Portfolio Rating) that allows for an immediate and consistent comparison with the benchmark.

Data and General Information

The analysis is based on a daily database downloaded from FactSet, covering the period between January 2007 and July 2025. For all securities and indices, we used the adjusted close value to properly account for splits and dividends in the price series. The universe includes the main asset classes and geographical areas, with liquid and investable instruments to ensure broad diversification (heterogeneous risks/drivers) and consistency with momentum, risk parity, and minimum-variance frameworks:

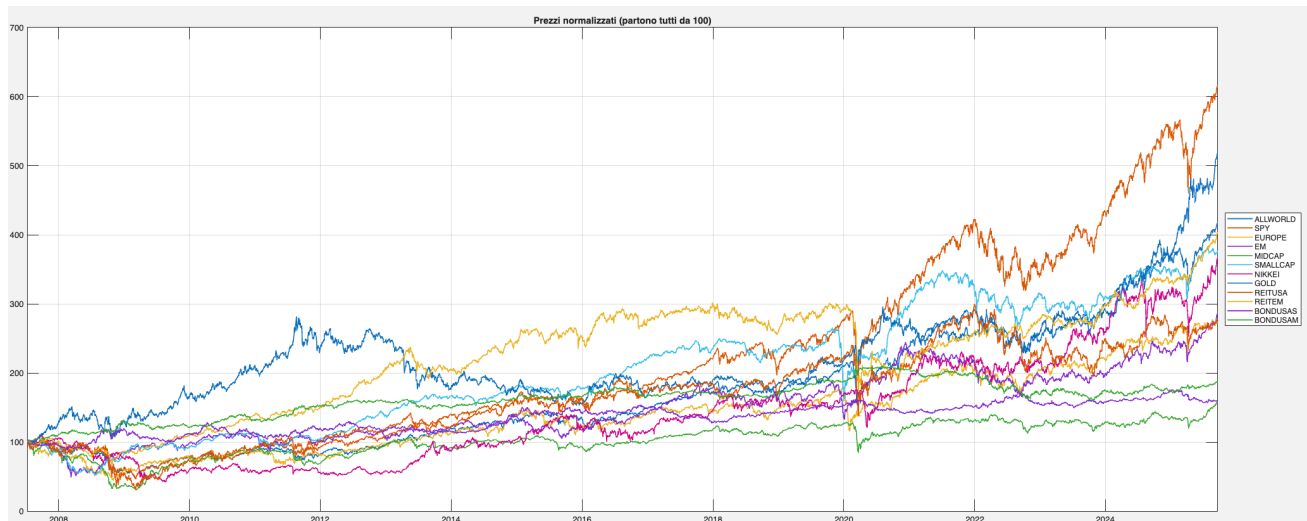
- Global Equity: FTSE All-World (AW01-FTX)
- Mid Cap Equity: FTSE ST Mid Cap Index (FSTM00000)
- Small Cap Equity: FTSE Small Cap (SMX.GBP-FTX)
- Emerging Markets Equity: MSCI Emerging Markets (EF-MSX)
- U.S. Equity: SPDR S&P 500 ETF Trust (SPY-USA)
- European Equity: STOXX Europe 600 (EUR) (SXXP-STX)
- Japanese Equity: Nikkei 225 (NIK-NKX)
- Gold: SPDR Gold Shares (GLD-USA)
- U.S. Government Bonds 1–3 years: iShares USD Treasury Bond 1–3yr UCITS ETF (IBTS-MIL)
- U.S. Government Bonds 7–10 years: iShares 7–10 Year Treasury Bond ETF (IEF-USA)
- U.S. REITs: Vanguard Real Estate ETF (VNQ-USA)
- Emerging Markets REITs: S&P Emerging Markets REIT (SBBREMREIT)

Why these assets? The set combines: (i) global equities for market beta (U.S., Europe, Japan, EM, size), (ii) government bonds with different durations for the defensive/rebalancing component, (iii) REITs for sectoral/real estate diversification, and (iv) gold as a macro hedge. The coverage is therefore multi-asset, multi-region, and multi-factor, with widely traded and transparent instruments suitable for testing dynamic allocation rules.

The series are aligned to the trading calendar, with precise handling of any short-horizon missing dates. Returns are always computed in logarithmic form. Decisions and rebalancing occur on a monthly frequency, while estimates (volatility, covariances, signals) are built on rolling daily data to enhance informational quality. Consequently, after the first month (identical by construction to the equal-weighted portfolio), all evaluations are out-of-sample relative to the estimation windows used for parameter

calculation. For comparison purposes, the benchmark is the equally weighted portfolio with monthly rebalancing, built on the same universe and using the same return convention (log).

The following figure illustrates the behavior of individual assets over time.



Portfolio Rating

To provide a synthetic, universal, and intuitive metric for comparing different strategies and portfolios, a proprietary indicator called Omega Portfolio Rating (OPR) has been developed.

The purpose of the OPR is to express, in percentage terms, the improvement or deterioration of a strategy relative to a reference benchmark – in this case, the Equally Weighted portfolio with monthly rebalancing – through a weighted combination of three independent measures of investment efficiency and robustness.

Specifically, the OPR represents the average percentage change across three selected metrics, designed to provide a comprehensive assessment of the strategy's risk-adjusted profile:

1. Calmar Ratio (S) – a well-established measure that expresses the ratio between the Compound Annual Growth Rate (CAGR) and the maximum drawdown; it evaluates the efficiency of returns adjusted for the maximum loss sustained.
2. Modified Sortino Ratio (C) – a variation of the traditional Sortino ratio, in which the denominator is not the standard deviation of negative returns but rather the

arithmetic mean of negative returns. This modification emphasizes the penalty due to the frequency and intensity of average losses rather than their variability.

3. Validity Index (R) – a newly designed indicator developed specifically to measure the stability and consistency of performance over time. Its numerator captures the cumulative return of the strategy excluding the top 1% of highest returns, thereby reducing the impact of isolated positive outliers. The denominator is the average between the maximum duration (in time) of drawdowns and the average drawdown duration observed throughout the sample, thus providing a time-based measure of risk.

The formula can be written like this:
$$\text{OPR} = \frac{1}{3} \left(\frac{S_p - S_b}{|S_b|} + \frac{C_p - C_b}{|C_b|} + \frac{R_p - R_b}{|R_b|} \right)$$

where:

- S_p , C_p , R_p are respectively the values of the first, second, and third metrics (in this case: Modified Sortino, Calmar Ratio, and Validity Index) for the strategy under analysis;
- S_b , C_b , R_b are the corresponding values of the benchmark strategy (Equally Weighted with monthly rebalancing);
- Each term of the sum represents the relative percentage variation of each metric with respect to the benchmark.

Taken together, these three components allow for an integrated evaluation of the strategy's ability to generate sustainable and consistent returns while simultaneously limiting exposure to prolonged drawdowns.

The final result of the Omega Portfolio Rating therefore provides a synthetic index (centered around zero) that enables an immediate and comparable assessment of how much a given strategy outperforms or underperforms the benchmark in terms of overall efficiency and resilience of its risk/return profile.

Since the main objective is the comparative evaluation of strategies and their combinations, the quantitative analyses are interpreted in a diagnostic rather than predictive perspective. The goal is to identify patterns of efficiency and dynamic behavior, not to construct an operational trading model.

Methodological framework and analytical setup

All strategies described in the following sections are implemented according to a coherent and comparable logic.

For each of them, portfolio weights are determined using only the information available at the time of rebalancing, in order to avoid any form of look-ahead bias.

Simulations are performed on an out-of-sample basis, and the first month – common to all strategies – coincides with the Equally Weighted portfolio, used as the starting point and reference benchmark.

The analyses focus exclusively on market dynamics, without including transaction costs, taxes, or other operational components.

This choice makes it possible to isolate the intrinsic behavior of the different allocation rules and to assess their effectiveness in purely mathematical and theoretical terms rather than operational ones; to apply the same analyses for practical implementation, it would be essential to include the asset turnover costs, which in any case have been minimized through the selection of low-cost instruments.

The strategies are therefore developed and compared following a progressive structure:

1. Base strategies, where each method is analyzed individually (EW, Risk Parity, Volatility Parity, Minimum-Variance, Mean-Variance, Momentum)
2. Combined strategies, where multiple rules are integrated to verify their joint effect on risk-adjusted performance
3. Adaptive strategies, where momentum and risk parity criteria are merged into a dynamic approach

For each approach, the following are computed:

- Portfolio returns and cumulative value (NAV)
- Main performance metrics (CAGR, volatility, Sharpe, Sortino, Calmar, drawdown)
- The Omega Portfolio Rating (OPR) relative to the monthly equally weighted benchmark

This methodological framework ensures that the results presented in the following sections are comparable, robust, and free from temporal distortions, allowing for an objective evaluation of the strategies in terms of efficiency and stability of the risk/return profile.

Considerations on in-sample and out-of-sample

In this study, no formal distinction was made between in-sample and out-of-sample periods. This choice is motivated by both technical and methodological considerations.

First, the available dataset covers the period 2007–2025, which, although sufficiently long for dynamic analysis, does not allow for an effective subdivision into two subperiods without compromising the statistical significance of performance metrics. A rigid separation of the sample would have reduced the analysis window for each phase, thereby limiting the robustness of return and risk measures – particularly for indicators such as Calmar, Sortino, and average drawdown, which require long observation series and complete market cycles to be representative.

Furthermore, no parameter optimization or “ex post” result selection process was performed. All strategies use fixed parameters (rolling daily windows, monthly or semiannual rebalancing) chosen in accordance with the theoretical rationale of each approach, and not based on ex post performance. This greatly reduces the risk of overfitting, i.e., tuning strategies to artificially maximize performance over a specific period.

The objective is therefore not to achieve the best possible historical performance, but to evaluate the relative consistency and robustness of the different strategies over time, within a realistic framework of limited data and stable parameters. This approach makes the results more representative of the strategies’ behavioral dynamics rather than of any optimization over an artificially selected time horizon.

Single Strategies

Equally Weighted Strategy

The Equally Weighted (EW) strategy represents the natural starting point for any asset allocation analysis, as it constitutes the most elementary and “neutral” form of diversification. In an equally weighted portfolio, each asset receives the same initial weight – for example, in the case of 10 instruments, each would have a 10% allocation – and this allocation is periodically rebalanced (in this case, on a monthly basis) to maintain equal exposure across assets. In other words, the strategy does not take into account volatility, correlations, momentum, or other specific characteristics of individual assets: it simply assigns equal importance to each security.

Conceptually, the EW approach is based on the idea that, in the absence of reliable forecasts for expected returns, a non-informed allocation is preferable – one that distributes both risk and capital equally across all available instruments. It is therefore a purely “agnostic” strategy: it does not seek to optimize but rather to avoid excessive concentration and subjective bias, while ensuring a minimum level of diversification. In this study, the equally weighted strategy is adopted as the benchmark for evaluating all other strategies.

Momentum Strategy

The Momentum strategy is based on the idea that assets which have performed well in the past tend, on average, to continue performing well in the near future. This phenomenon, widely documented in empirical literature (Jegadeesh and Titman, 1993), reflects a recurring feature of financial markets related to price inertia, behavioral dynamics of investors, and delays in information adjustment.

Operationally, the strategy computes for each asset the cumulative logarithmic return over a rolling window of 63 days (approximately three months of trading), using only past data to avoid any form of look-ahead bias. At the end of each month, instruments are ranked according to this momentum score, and the group of Top-K assets with the strongest relative performance is selected. Capital is then allocated equally among the selected securities, while the remaining assets are excluded from the portfolio until the next rebalancing.

In questo paper andremo ad analizzare due distinte versioni di questa strategia, entrambe utilizzando la medesima formula, ovvero la somma dei rendimenti per la finestra selezionata, ma in una versione andremo a ignorare le osservazioni più recenti per concentrarsi sul momentum presente precedentemente.

Mean-Variance Strategy

The Mean-Variance strategy is based on the principles of Markowitz's modern portfolio theory. The goal is to construct portfolios that offer the best possible balance between expected return and estimated risk, based on the most recent historical data. In practice, at each monthly rebalancing, the mean and covariance of logarithmic returns are calculated over a rolling window of daily data, which are then used to determine the optimal asset weights.

In our case, the strategy is long-only and fully invested, meaning that all weights are non-negative and sum to one, making it directly comparable with the Equally Weighted benchmark. The estimates used for optimization are always out-of-sample, i.e., based only on information available up to the previous month, in order to avoid any form of look-ahead bias.

The Mean-Variance framework represents the classical reference for optimized allocation models, but it is also known for its sensitivity to estimation errors – particularly in expected returns – which can lead to unstable or overly concentrated portfolio weights.

Minimum Variance Strategy

The Minimum Variance strategy represents a simplified and more robust version of the Markowitz model. Unlike the Mean-Variance approach, it does not require estimating the expected returns of the assets – often a major source of uncertainty – but focuses solely on the risk component, aiming to minimize the total variance of the portfolio.

In practical terms, at each monthly rebalancing, rolling covariances of daily logarithmic returns are computed over a moving window, and weights are determined to achieve the combination of assets with the lowest possible volatility, subject to full investment and long-only constraints. In this way, the strategy emphasizes stability and capital preservation, foregoing any explicit return objective.

L'approccio Minimum Variance è particolarmente adatto in contesti di alta incertezza o bassa prevedibilità dei rendimenti, dove stimare le performance future risulta difficile. La strategia tende a favorire gli asset meno volatili e scarsamente correlati tra loro,

producendo portafogli più stabili nel tempo, con drawdown generalmente più contenuti rispetto a strategie orientate al rendimento.

Risk Parity Strategy

The Risk Parity strategy is based on the idea of distributing each asset's contribution to total portfolio risk equally, rather than allocating the same amount of capital as in the Equally Weighted approach. In other words, every instrument contributes equally to the overall portfolio volatility, regardless of its nominal weight.

The purpose of the Risk Parity approach is to construct more stable and diversified portfolios, in which no single asset dominates overall performance. It is particularly effective in multi-asset contexts, where instruments with different volatility and correlation profiles (e.g., equities, bonds, gold, real estate) allow for a more efficient distribution of risk than a simple uniform allocation.

Compared with the Equally Weighted benchmark, the Risk Parity strategy tends to generate lower volatility and more consistent returns, though it may sacrifice part of the performance during strongly bullish market phases.

Volatility Parity Strategy

The Volatility Parity strategy is based on the objective of allocating capital so that each asset contributes equally to the overall portfolio volatility. In other words, the goal is not to equalize risk contributions in terms of risk budget (as in Risk Parity), but rather to distribute exposures in inverse proportion to each asset's expected volatility.

The underlying idea is that, in a multi-asset portfolio context, more volatile instruments tend to dominate total risk if weighted equally. To prevent this, Volatility Parity assigns weights proportional to the inverse of the estimated volatility.

The logic of Volatility Parity lies halfway between the simplicity of the Equally Weighted approach and the sophistication of Risk Parity. However, while it ensures a certain degree of stability, it tends to be less effective during periods of strong dispersion among asset classes, as it considers only the individual risk of each asset and not the correlations between them.

Combined Strategies

Combined Strategy 1 - Technical Analysis (Moving Average + RSI)

The first combined strategy introduced in this study is inspired by principles of technical analysis rather than by optimization or risk-balancing models. Although not included in the reference papers, it was added to provide a practical comparison illustrating how simple and widely used tools among discretionary traders can be employed within a structured quantitative framework.

The construction logic is twofold. First, a trend filter is applied: only assets whose prices are above their annual moving average (calculated over a rolling window of approximately 252 trading days) are selected. This ensures that the portfolio invests exclusively in instruments exhibiting a positive medium-to-long-term trend, while excluding those in a bearish phase.

Next, within the set of selected assets, portfolio weights are assigned inversely proportional to the RSI (Relative Strength Index) value. This means that assets with a lower RSI – those less “overheated” and potentially entering a rebound phase – receive a higher weight, whereas assets with higher RSI values, possibly in overbought conditions, are penalized.

The underlying idea is to combine two complementary signals: the directional filter of the moving average, which identifies the prevailing trend, and the RSI indicator, which measures short-term relative strength or weakness. Together, these tools aim to construct a portfolio that favors assets in an upward trend but still offering technical “breathing room,” thereby reducing the likelihood of entering at overextended levels.

Although based on simple rules without complex parameters, this strategy provides an interesting benchmark against more theoretical models (Momentum, Risk Parity, Mean-Variance), demonstrating how approaches derived from technical analysis can also produce systematic and interpretable behaviors within a quantitative framework.

Combined Strategy 2 - Lagged Momentum with Risk Parity

The second combined strategy integrates two distinct approaches: momentum-based selection and risk-based weighting. The objective is to combine the momentum’s ability to identify assets with stronger relative performance with the stability and diversification characteristic of the Risk Parity framework.

The selection mechanism employs lagged momentum, defined as the cumulative (logarithmic) return calculated over a past observation window – for example, one quarter – while excluding the most recent month from the computation. This choice removes short-term effects often dominated by noise or technical reversals and allows for the capture of more structural trends. At the end of each month, the six assets with the highest lagged momentum are identified, forming the investable subset for the next period.

Once the assets have been selected, the weighting phase follows the Risk Parity principle: weights are determined so that each asset contributes equally to the total portfolio risk. This implies that more volatile instruments receive lower weights, while more stable ones are assigned higher weights, ensuring a balanced overall risk distribution within the selected group.

This combination of rules leverages two complementary dimensions:

- The directional component, captured by lagged momentum, which favors assets showing positive medium-term trends;
- The stability component, introduced through risk parity, which prevents a small number of assets from dominating total portfolio risk.

The “Lagged Momentum + Risk Parity” strategy therefore aims to construct a dynamic yet balanced portfolio, capable of adapting to changing market trends while maintaining a controlled risk profile. Within the context of this study, it represents a transitional point between purely directional frameworks (such as Momentum) and purely risk-based approaches (such as traditional Risk Parity).

Combined Strategy 3 - Momentum with Volatility Parity

The third combined strategy integrates the classical momentum component with a Volatility Parity framework for weight determination. The goal is to combine the momentum’s ability to select assets with superior recent performance with an allocation mechanism that balances the portfolio based on volatility, thereby reducing the impact of riskier assets.

The selection phase is based on standard momentum, calculated as the cumulative logarithmic return over a rolling window of approximately three months (63 trading days). Unlike the lagged version, this analysis includes the most recent period, allowing the model to capture the most up-to-date strength of market trends. At the end of each

month, the six assets with the highest momentum are selected to form the portfolio for the following month.

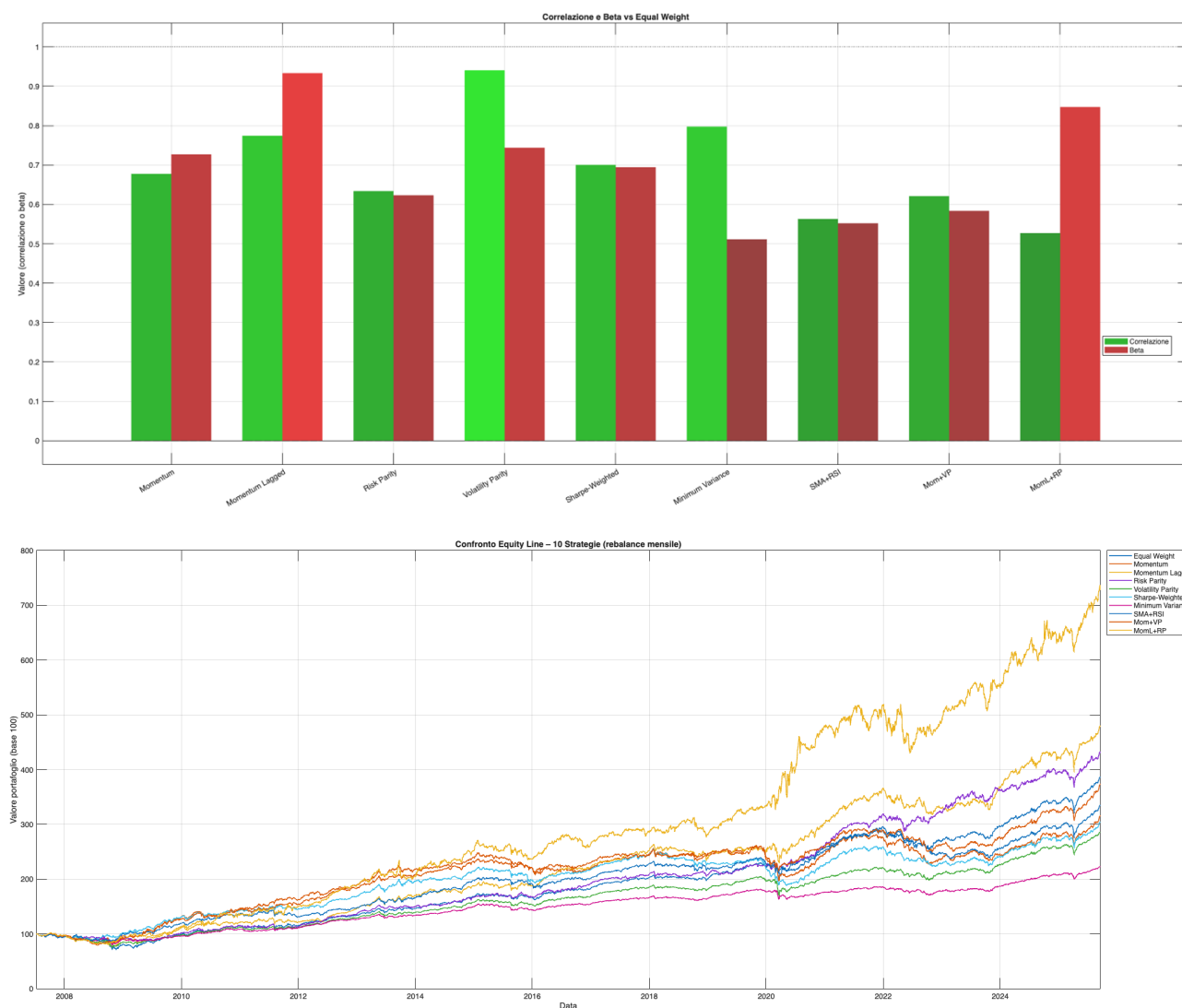
Once the assets are selected, the weighting phase applies the Volatility Parity criterion, according to which weights are inversely proportional to the estimated volatility of each asset. In practice, more volatile instruments receive a smaller allocation, while more stable ones are assigned a higher weight. Volatility is estimated on a rolling daily basis, ensuring that the weighting reflects the most recent market conditions.

The combination of these two components results in a strategy that seeks to dynamically optimize the risk/return trade-off: momentum identifies the assets with the most favorable trends, while volatility parity controls overall risk exposure, preventing excessive concentration.

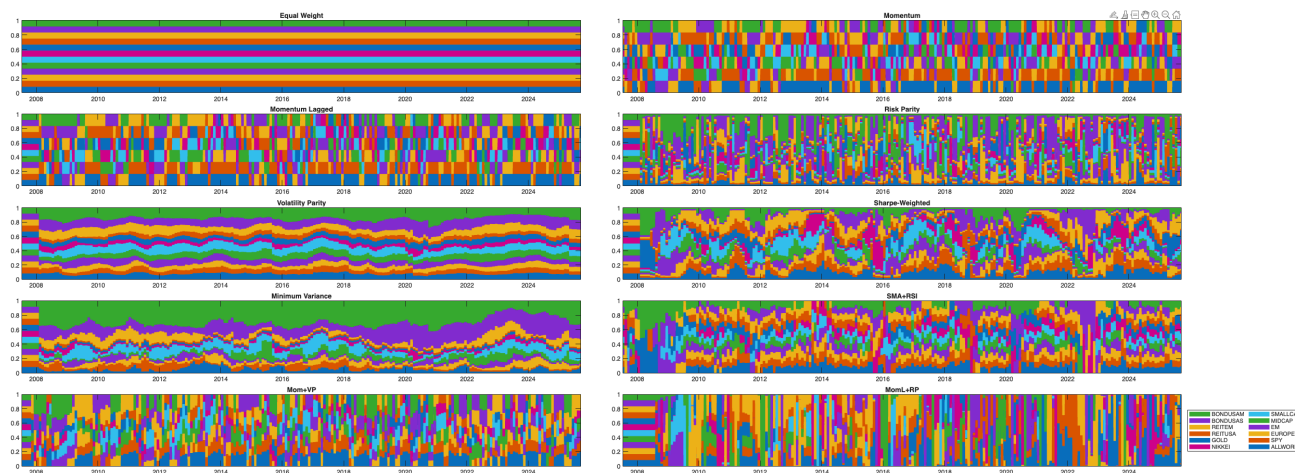
Within the context of this work, the “Momentum + Volatility Parity” strategy represents a balanced and pragmatic approach that merges a proactive directional logic with disciplined risk management, offering a synthesis between purely trend-following strategies and those based solely on risk-balancing criteria.

Performance Analysis

From the chart presented here, we can observe that although the dynamics governing the allocation of weights across different assets vary significantly depending on the strategy, they consistently maintain a close alignment with the benchmark, showing an average correlation of 0.7 and an average Beta of 0.69.



In the following figure, we can analyze the temporal distribution of portfolio weights across the different strategies. It is important to note that in all cases there is a period—ranging from 1 to 6 months depending on the specific characteristics of each strategy—during which the weights coincide with those of the benchmark strategy. This occurs because that initial time window is used to compute the metrics that subsequently determine the asset allocation.



It is important to note that among all the strategies, those exhibiting the greatest variability in portfolio weights are the ones incorporating momentum rules and the Risk Parity strategy. This characteristic implies that these four strategies – which are also the only ones to have outperformed the benchmark (as determined by the Omega metric) – would be the most affected by transaction costs arising from their high portfolio turnover, thereby reducing the advantage they have achieved.

Strategy	Omega	CAGR	AnnVol	Sharpe	Sortino	MaxD	Kalmar	WorstM	Var 99%
Risk Parity	0,53	8,38%	6,82%	1,22	1,65	17,48%	0,48	-8,52%	1,17%
MomL+RP	0,35	11,57%	11,15%	0,98	1,26	21,34%	0,54	-6,10%	1,90%
Mom+VP	0,21	7,51%	6,52%	1,14	1,58	22,52%	0,33	-7,78%	1,14%
SMA+RSI	0,19	7,46%	7,08%	1,05	1,41	19,08%	0,39	-5,17%	1,28%
Momentum Lagged	0,12	9,01%	8,37%	1,03	1,35	24,84%	0,36	-6,80%	1,50%
Equal Weight	0,00	7,71%	6,94%	1,07	1,38	30,18%	0,26	-11,21%	1,19%
Momentum	-0,08	6,53%	7,45%	0,85	1,14	24,71%	0,26	-9,99%	1,34%
Volatility Parity	-0,11	5,95%	5,49%	1,08	1,35	26,62%	0,22	-8,85%	0,94%
Mean Variance	-0,23	6,30%	6,88%	0,92	1,23	26,09%	0,24	-7,25%	1,27%
Minimum Variance	-0,25	4,50%	4,45%	1,01	1,32	21,86%	0,21	-7,38%	0,78%

The analysis of the metrics highlights significant differences among the strategies considered, both in terms of absolute returns and risk-adjusted efficiency. Among the single strategies, Risk Parity clearly stands out with the highest Omega Portfolio Rating (0.53) and the best overall efficiency indicators, such as Sharpe (1.22) and Sortino (1.65),

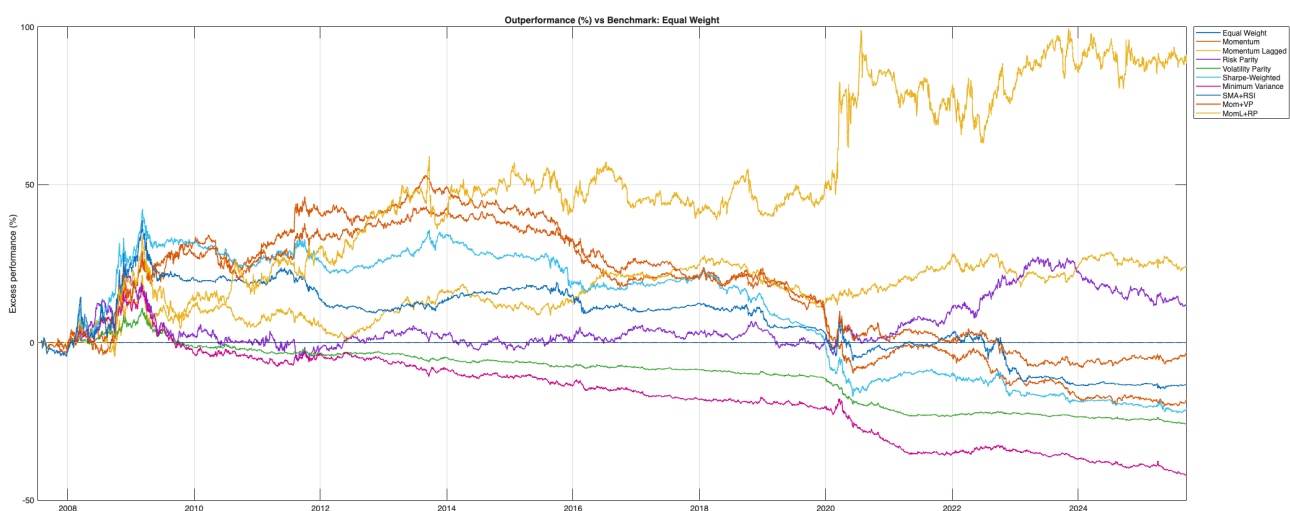
accompanied by a relatively limited maximum drawdown (−17.48%). This confirms the ability of this approach to stabilize returns through a balanced distribution of risk across assets.

The Momentum Lagged + Risk Parity (MomL+RP) strategy ranks as the best among the combined adaptive strategies, with a CAGR of 11.57% – the highest in the sample – and a positive Omega (0.35), indicating a clear improvement over the benchmark, despite exhibiting higher volatility (11.15%). The combination of lagged momentum (which filters out short-term noise from the most recent month) and risk-based weighting produced a robust and well-diversified return profile.

The Momentum + Volatility Parity (Mom+VP) and SMA + RSI strategies also show consistent results, with positive Omega values (0.21 and 0.19) and solid efficiency ratios (Sortino > 1.4), demonstrating the effectiveness that even simple technical analysis rules can achieve.

Purely directional versions, such as Momentum and Lagged Momentum, deliver strong returns but with higher volatility and drawdowns, revealing greater sensitivity to market cycles.

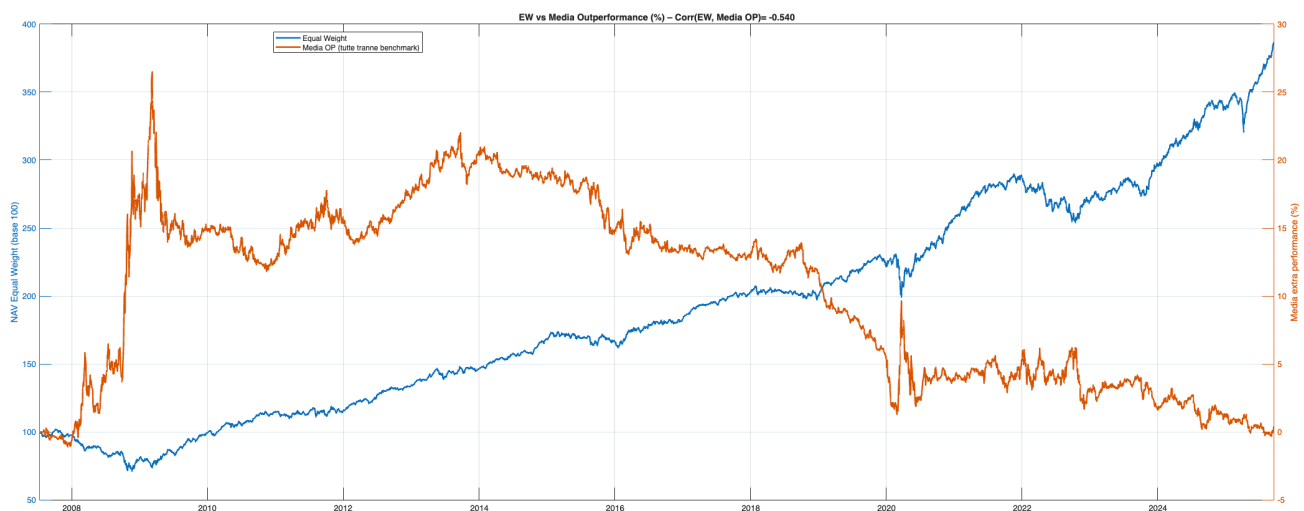
Conversely, the Volatility Parity, Mean-Variance, and Minimum Variance strategies show negative OPR values, reflecting underperformance relative to the benchmark, particularly in terms of average return and Calmar ratio. These results confirm that an excessive focus on minimizing risk alone can hinder portfolio growth, especially during pronounced directional market phases.



The figure just presented shows the percentage excess performance of the various strategies relative to the benchmark. One of the most interesting insights is the behavior that the strategies, as a whole, exhibit following periods of market crashes, where they tend to lose relative performance simultaneously. This indicates that after a downturn, the dynamics required to predict which asset or asset class will outperform in the future become substantially more complex and demand analytical approaches beyond those explored in this study.

In contrast, the two moments in which the different strategies gain an advantage are precisely during flash crashes—where a risk-oriented allocation of portfolio weights helps to contain losses—and during prolonged directional trends, where momentum-based strategies manage to generate excess performance.

Once again, this brings us back to one of the central themes of financial markets: the need—and at the same time the near impossibility—to forecast future market regimes rather than simply identifying the “best” individual strategy.



Supporting this thesis, the figure shown above displays in blue the EW strategy used as the benchmark and in orange the average percentage excess performance across all analyzed strategies. The correlation coefficient between the returns of these two time series stands at -0.54.

The negative correlation value therefore confirms that the analyzed strategies are not merely leveraged versions of the benchmark, but rather complementary alternatives capable of providing diversification and protection during periods of market stress.

Conclusions

Based on the analyses conducted so far, we can state that among the classical portfolio construction models, the rules combining momentum dynamics with volatility-based asset allocation tend to exhibit a higher annual return profile, at the cost of higher risk measures (such as VaR, worst month, and annual volatility). This contrasts with strategies such as Volatility Parity, Mean-Variance, and Minimum Variance, which generally show a lower risk-return profile than the benchmark, despite displaying slightly lower risk metrics. Among the single-rule approaches, the Risk Parity strategy stands out, as it has been shown to enhance portfolio performance even when combined with momentum-based logic.

The results obtained here are derived from a specific set of assets and a well-defined time horizon. Although these two variables were chosen to be representative in most cases, every strategy and operational methodology should be carefully re-evaluated depending on the asset universe employed, since the metrics presented here may vary over time due to the inherently changing nature of financial markets.

In light of this, it is essential to be fully aware of the precise strengths and weaknesses of any strategy intended for use in the financial markets, in order to be prepared to withstand its critical phases and to maintain expectations consistent with the analyses performed.

In conclusion, I would like to emphasize the crucial importance that every market participant should place on the study and evaluation of the operational methodology they intend to apply—focusing not only on identifying the strategy that appears best “on paper” through risk-adjusted metrics, but also on finding the one that best fits the investor’s individual risk tolerance and behavioral traits. In this sense, one should aim to develop a *tailor-made approach to finance* that best suits one’s own professional identity as an investor.