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ROBUSTNESS OF ASSET ALLOCATION STRATEGIES IN LONG-TERM INVESTING: A COMPARATIVE ANALYSIS OF SELECTED PORTFOLIO APPROACHES

ROBUSTNOSŤ STRATÉGIÍ ALOKÁCIE AKTÍV PRI DLHODOBOM INVESTOVANÍ: KOMPARÁCIA VYBRANÝCH PORTFÓLIOVÝCH PRÍSTUPOV

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Abstract: *This paper examines the robustness of selected asset allocation strategies in the context of long-term investing. The study compares the performance and risk characteristics of four portfolio construction approaches – the 1/N portfolio, the 60/40 portfolio, the annually rebalanced Markowitz portfolio (MW+R) and a portfolio with weights directly proportional to asset volatility (SD) – over 10- and 20-year investment horizons. The empirical analysis is based on weekly data for nine exchange-traded funds representing different asset classes over the period 2009–2025. Historical backtesting is complemented by Monte Carlo simulations employing a bootstrap approach to evaluate the stability and resilience of the strategies under alternative market scenarios. The results show that no single strategy dominated in all indicators: the SD portfolio achieved the highest returns, whereas the constrained Markowitz portfolio provided the most favourable risk-adjusted performance and ranked first in the composite robustness assessment in all simulation scenarios and at both horizons, while the 1/N strategy remained a competitive simple alternative. The study thus contributes to the literature on long-term portfolio management by comparing simple allocation rules with optimization-based approaches and provides practical implications for strategic asset allocation in dynamically changing financial markets.*
Keywords: asset allocation, portfolio optimization, long-term investing, portfolio robustness, risk-adjusted performance, Monte Carlo simulation
JEL Classification: C15, G11, G15, G17

INTRODUCTION

Asset allocation is among the most important determinants of the long-term performance of an investment portfolio. The decision on how to distribute capital across asset classes explains a substantial proportion of the variability in portfolio returns, whereas security selection and market timing generally play a smaller role. Long-term investors nevertheless face fundamental uncertainty because future asset returns, volatilities, and correlations are unknown, and estimates based on historical data are subject to error. The sensitivity of optimization models to the quality of input estimates therefore raises the question of whether sophisticated portfolio-construction approaches genuinely create more value for investors than simple allocation rules. This paper aims to assess the robustness of four asset allocation strategies in long-term investing: the equally weighted 1/N portfolio, the traditional 60/40 portfolio, a Markowitz portfolio with regular annual rebalancing (MW+R), and a dynamic portfolio with weights directly proportional to asset volatility (SD). Robustness is understood not merely as achieving the highest return, but as a strategy's ability to deliver stable risk-adjusted performance, adequate downside protection, and consistent results across different market conditions and investment horizons.

The empirical analysis draws on weekly data for nine exchange-traded funds representing the principal asset classes over the period 2009–2025. Historical backtesting is complemented by Monte Carlo simulations based on bootstrap resampling of historical observations, allowing the behaviour of the strategies to be evaluated over 10- and 20-year investment horizons across thousands of alternative market scenarios. Combining the two approaches reduces the risk that the conclusions are conditional on a single realized historical period. The paper consists of an introduction and four subsequent sections. Section 1 summarizes the theoretical foundations of modern portfolio theory, diversification, and the assessment of investment-strategy robustness. Section 2 describes the selection of financial instruments, the construction of the portfolios under comparison, and the methods used to evaluate their performance and risk. Section 3 presents and discusses the results of the historical backtest, Monte Carlo simulations, and robustness analysis. The conclusion summarizes the main findings, limitations, and avenues for further research.

1 THEORETICAL BACKGROUND

Investment decision-making is the process of allocating capital among financial assets with different return and risk profiles. As Koumou (2020) notes, the portfolio approach assumes that investors should not evaluate instruments in isolation, but in terms of their contribution to the portfolio's overall return and risk. Diversification—the allocation of capital across assets with different characteristics and interrelationships—is a key risk-management tool. Its principal benefit lies in reducing unsystematic risk specific to individual companies, sectors, or regions. Diversification cannot, however, fully eliminate systematic risk arising from broad financial-market developments. Portfolio risk is therefore not the simple sum of the risks of its individual components; rather, it is determined by their volatilities, weights, and pairwise correlations.

The theoretical foundation of modern portfolio management is Markowitz theory, also known as the mean–variance approach. Markowitz (1952) assumes that investors consider expected return and risk, expressed as the variance or standard deviation of returns, when making decisions. Optimization seeks a combination of assets that maximizes expected return for a specified level of risk or, alternatively, minimizes risk for a required return. A key contribution of the Markowitz model is its incorporation of covariances between assets, which captures the diversification effect and enables the construction of efficient portfolios (Mangram, 2013). Closely related to Markowitz theory is the concept of the efficient frontier, which represents the set of portfolios offering the best attainable risk–return trade-off. The efficient frontier does not, however, identify a universally optimal portfolio, because the choice of a particular allocation depends on the investment horizon, return objectives, and the investor's degree of risk aversion. In practice, its application is constrained by sensitivity to the quality of the input data. Small changes in estimated expected returns, volatilities, or correlations can produce markedly different optimal weights. Classical optimization also abstracts from several practical factors, including transaction costs, liquidity constraints, taxes, and short-sale restrictions. Modern approaches therefore seek to stabilize input estimates and impose more practical constraints on portfolio weights (Hodnett, 2012; Guo, 2022; Salo et al., 2024). The equally weighted 1/N strategy is an important benchmark for assessing optimization-based approaches. Its principal advantages are simplicity, transparency, and the absence of any need to forecast future returns, volatilities, or covariances. DeMiguel et al. (2009) showed that simple naive diversification can, in practice, perform as well as or better than a range of sophisticated optimization models. The main reason is estimation error in the input parameters, which can reduce the practical effectiveness of complex models. Comparing simple and optimization-based approaches is therefore relevant not only in terms of realized returns, but also with respect to the stability and practical implementability of the resulting portfolios.

Long-term portfolio performance is also affected by the selected allocation strategy and the way in which it is maintained over time. Strategic asset allocation refers to the long-term distribution of capital across asset classes according to the investor's objectives, investment horizon, and risk tolerance. Unlike tactical allocation, it does not focus on short-term forecasts of market movements but on establishing a stable portfolio framework. Tactical allocation, by contrast, involves more flexible adjustments to weights in response to expected changes in market conditions, macroeconomic indicators, or asset valuations (Anson, 2004; Eychenne et al., 2011; Lumholdt, 2018). Over time, however, the original portfolio weights naturally change because assets perform differently. Rebalancing restores the target allocation and preserves the intended risk profile of the portfolio. Annual or semi-annual rebalancing may offer a reasonable compromise between risk control and the containment of transaction costs and administrative burden (Zilbering et al., 2015). Under certain conditions, rebalancing may also generate a rebalancing premium, as the investor systematically reduces the weights of assets that have appreciated strongly and increases those of relatively underperforming assets. This effect is not automatic; it depends on volatility, correlations, rebalancing frequency, and trading costs (Maeso and Martellini, 2020).

The evaluation of portfolio strategies must also reflect the instability of financial markets. Asset returns frequently depart from the normal distribution: they may be asymmetric, exhibit excess kurtosis, and contain extreme observations more often than traditional models assume. Volatility clustering is another important phenomenon, whereby periods of elevated volatility are concentrated and persistent. Portfolio risk is therefore not constant over time, and realized performance may be materially affected by the prevailing market regime or the timing of the investment (Eom, Kaizoji, and Scalas, 2019; Lukanima and Swaray, 2013; Zhao et al., 2024). For these reasons, evaluating a portfolio solely on the basis of its average return or the outcome of a single historical period is inappropriate. Strategy robustness may be understood as the capacity to achieve satisfactory risk-adjusted performance, acceptable protection against adverse outcomes, and relatively stable results across different market conditions. In this context, it is relevant to compare outcomes across investment horizons, since a longer horizon may reduce the influence of short-term fluctuations while also magnifying the consequences of a poorly specified allocation or risk concentration.

Monte Carlo simulation provides a complementary assessment tool by generating a large number of alternative return paths and allowing the full distribution of possible portfolio outcomes to be examined. Unlike historical backtesting alone, it facilitates the evaluation of uncertainty, the probability of adverse outcomes, and the variability of the investment's future value. Simulations cannot, however, be interpreted as precise forecasts, because their results are always conditional on historical data and the chosen model assumptions. Their purpose is to supplement historical analysis with a broader view of how portfolio strategies may behave under different scenarios (Antonov and Demirova, 2023; Karminsky and Seryakova, 2015). These theoretical considerations underpin the empirical analysis, which compares the robustness of four asset allocation strategies over 10- and 20-year investment horizons. Attention is paid not only to realized returns, but also to risk-adjusted performance, downside risk, maximum drawdown, and the stability of results across historical and simulated scenarios.

2 METHODOLOGY

The empirical analysis aims to assess the robustness of selected asset allocation strategies in long-term investing. Robustness is defined as the ability of a strategy to deliver stable risk-adjusted performance, adequate downside protection, and relatively consistent results across different investment horizons and market scenarios. Four strategies are compared: the equally weighted 1/N portfolio, the traditional 60/40 portfolio, the SD portfolio based on weights directly proportional to asset volatility, and a regularly rebalanced Markowitz portfolio, denoted MW+R.

2.1 Selection of Financial Instruments and Portfolio Construction

The sample consists of nine exchange-traded funds representing the principal segments of global financial markets. It covers U.S., European, and emerging equity markets, corporate and government bonds, money-market instruments, gold, and real estate. All selected financial instruments were converted into U.S. dollars. When combined under the different investment strategies, these assets provide sectoral diversification by incorporating both growth-oriented and defensive asset classes.

Table 1: Selected asset classes used in portfolio construction and the benchmark1

Asset class	ETF ticker	ETF name
U.S. large-cap equities	SPY	SPDR S&P 500 ETF Trust
U.S. small-cap equities	IJR	iShares Core S&P Small-Cap ETF
European equities	VGK	Vanguard FTSE Europe ETF
Emerging-market equities	EEM	iShares MSCI Emerging Markets ETF
Corporate bonds	LQD	iShares iBoxx $ Investment Grade Corporate Bond ETF
Long-term U.S. Treasuries	TLT	iShares 20+ Year Treasury Bond ETF
Treasury Bills/cash proxy	BIL	SPDR Bloomberg 1-3 Month T-Bill ETF
Gold	GLD	SPDR Gold Shares
Real Estate	VNQ	Vanguard Real Estate ETF
Benchmark	ACWI	iShares MSCI ACWI ETF

Source: Authors' compilation based on publicly available data from Yahoo Finance and the websites of the respective asset-management companies (2026).

The input data consisted of adjusted closing prices for the ETFs, which account for dividends, stock splits, and other corporate actions. All data were expressed in U.S. dollars without currency hedging. Weekly returns were calculated from daily prices, with the return on ETF i in period t defined as follows:

$$r_{i,t} = \frac{P_{i,t}}{P_{i,t-1}} - 1 \quad (1)$$

where $r_{i,t}$ denotes the weekly return on the ETF, $P_{i,t}$ is its adjusted closing price in the current week, and $P_{i,t-1}$ is its price in the preceding week.

The weekly return on each portfolio was calculated as the weighted average of the returns on all ETFs:

$$r_{p,t} = \sum_{i=1}^{N} w_{i,t-1} r_{i,t} \tag{2}$$

where $r_{p,t}$ is the portfolio return in period t, $w_{i,t-1}$ is the asset weight at the beginning of that period, and N is the number of ETFs.

Under the 1/N strategy, capital was allocated equally across all nine ETFs. The equally weighted portfolio follows the naive-diversification rule, under which capital is divided evenly among all assets (DeMiguel et al., 2009):

$$w_i = \frac{1}{N} \tag{3}$$

where N = 9, so each ETF has an initial weight of 11.11%. The strategy serves as a benchmark for simple diversification and does not rely on forecasts of returns, volatilities, or correlations among assets.

The 60/40 portfolio followed the traditional allocation of capital between growth-oriented and more conservative components. Each of the equity ETFs—SPY, IJR, VGK, and EEM—received a weight of 15%, together constituting 60% of the portfolio. The remaining 40% was allocated equally among LQD, TLT, BIL, GLD, and VNQ, each with a weight of 8%.

$$w_{equity} = \begin{bmatrix} w_{SPY|equity} \\ w_{IJR|equity} \\ w_{VGK|equity} \\ w_{EEM|equity} \end{bmatrix} = \begin{bmatrix} 0.15 \\ 0.15 \\ 0.15 \\ 0.15 \end{bmatrix} \tag{4}$$

$$w_{defensive} = \begin{bmatrix} w_{LQD|defensive} \\ w_{TLT|defensive} \\ w_{BIL|defensive} \\ w_{GLD|defensive} \\ w_{VNQ|defensive} \end{bmatrix} = \begin{bmatrix} 0.08 \\ 0.08 \\ 0.08 \\ 0.08 \\ 0.08 \end{bmatrix} \tag{5}$$

where w_{equity} denotes the set of weights assigned to the equity ETFs, and $w_{defensive}$ denotes the set of weights assigned to the ETFs representing the defensive component.

In the SD portfolio, weights were set directly in proportion to the standard deviation of each ETF's returns over the preceding 52 weeks. Riskier assets therefore received a larger portfolio allocation:

$$w_{i,t} = \frac{\sigma_{i,t-1}}{\sum_{j=1}^{N} \sigma_{j,t-1}} \tag{6}$$

where $\sigma_{i,t-1}$ is the standard deviation of the weekly returns on ETF i, calculated from data available before the beginning of the new period. This weighting scheme is deliberately unconventional: in contrast to the more common inverse-volatility (risk-parity-type) rules, which allocate more capital to less volatile assets, the SD portfolio inverts this logic. Its inclusion is motivated by the aim of adding an aggressive, return-seeking benchmark to the strategy set and of testing directly whether systematically greater exposure to more volatile assets is adequately compensated by higher returns over long investment horizons.

The MW+R strategy was constructed using the mean–variance optimization framework formulated by Markowitz (1952). The objective was to maximize expected return while keeping risk at a level no higher than the volatility of the 1/N portfolio. The optimization problem was formulated as follows:

$$\max_{w} \; w^T \mu \tag{7}$$

subject to:

$$w^T \sum w \leq \sigma_{1/N}^2$$

$$\sum_{i=1}^{N} w_i = 1$$
$$0 \leq w_i \leq 0.15$$

where w is the vector of portfolio weights, μ is the vector of expected returns, Σ is the covariance matrix of returns, and $\sigma_{1/N}^2$ is the variance of the equally weighted portfolio. The 15% maximum-weight constraint prevents excessive concentration in a single ETF, while the non-negativity constraint rules out short selling.

To ensure comparability across strategies, rebalancing was performed at the beginning of each calendar year. For the 1/N and 60/40 strategies, the original target weights were restored. For the SD portfolio, weights were recalculated using volatility over the preceding year. For MW+R, the vector of expected returns and the covariance matrix were re-estimated as the sample mean vector and the sample covariance matrix of weekly returns over the preceding 52 weeks, the new optimal weights were recomputed, and the portfolio was likewise rebalanced annually. This design ensured that the 60/40 portfolio remained a genuine 60/40 portfolio throughout the analysis and that differences in outcomes were not driven solely by a gradual drift in weights.

2.2 Evaluation of Strategy Performance and Robustness

Portfolio performance was evaluated using a combination of historical backtesting and Monte Carlo simulation. The historical backtest assessed the behaviour of the strategies using actually observed ETF returns, while the simulations extended the analysis to a large number of possible future scenarios. This dual approach is particularly suitable for evaluating robustness because it does not assess a strategy solely on the basis of one historical period or a single realized outcome.

The cumulative portfolio value was used as the basic measure of long-term performance:

$$V_T = V_0 \prod_{t=1}^{T} (1 + r_{p,t}) \tag{8}$$

where V_0 is the initial value of the investment and V_T is its value at the end of the investment horizon. To compare results across horizons of different lengths, the compound annual growth rate was used:

$$CAGR = \left(\frac{V_T}{V_0}\right)^{\frac{52}{T}} - 1 \tag{9}$$

where T denotes the number of weeks in the analysed horizon. For the 10-year horizon, $T = 520$, and for the 20-year horizon, $T = 1\,040$.

Portfolio risk was measured by annualized volatility:

$$\sigma_p = SD(r_p)\sqrt{52} \tag{10}$$

Risk-adjusted performance was evaluated using the Sharpe and Sortino ratios. The Sharpe ratio (Sharpe, 1994) expresses the portfolio's excess return relative to its total volatility:

$$SR = \frac{\overline{r_p - r_f}}{\sigma_p} \tag{11}$$

where $\overline{r_p - r_f}$ is the portfolio's mean excess return over the risk-free rate, and σ_p is the annualized portfolio volatility. Three-month U.S. Treasury bills were used as the risk-free rate because the BIL ETF is itself included in the investment universe from which the portfolios were constructed.

The Sortino ratio (Sortino and Price, 1994) accounts only for negative deviations in returns:

$$Sortino = \frac{\overline{r_p - r_f}}{DD_p} \tag{12}$$

where DD_p is the portfolio's downside deviation. This measure is particularly suitable because investors generally do not regard upside volatility as risk.

The supplementary risk measures were maximum drawdown, Value at Risk, and Expected Shortfall. Maximum drawdown was measured as the largest decline in portfolio value from a previous peak (Chekhlov et al., 2005):

$$MDD = \min_{t}\left(\frac{V_t}{\max_{T\leq t} V_t} - 1\right) \tag{13}$$

Value at Risk and Expected Shortfall were calculated at the 95% confidence level following Rockafellar and Uryasev (2000). VaR represents the threshold of an adverse loss at a given percentile of the outcome distribution, whereas Expected Shortfall captures the average loss in the worst 5% of cases.

To quantify the risk of extreme losses, we use VaR_a (Value at Risk) and ES_a (Expected Shortfall), annualized in both cases. Both metrics are estimated using historical simulation applied to the distribution of annual portfolio returns. VaR represents the maximum expected loss at a given confidence level and is defined as follows:

$$VaR_\alpha = -q_{1-\alpha}(R) \tag{14}$$

where VaR_a denotes Value at Risk at confidence level α, $q_{1-\alpha}(R)$ is the empirical quantile of the return distribution, R is a random variable representing the portfolio return, and α is the confidence level (0.95). ES, which complements VaR, provides the average loss conditional on exceeding the VaR threshold and is defined as follows:

$$ES_\alpha = -E[R|R \leq q_{1-\alpha}(R)] \tag{15}$$

where ES_a denotes Expected Shortfall at confidence level α, $E[\cdot]$ is the expectation operator, R is the portfolio return, and $\mathrm{q}_{1-\mathrm{a}}(R)$ is the corresponding quantile of the return distribution.

The Monte Carlo simulation was based on bootstrap resampling of historical weekly returns. Unlike parametric simulations, it did not assume normally distributed returns. At each simulation step, the entire nine-dimensional vector of weekly ETF returns was randomly sampled. This procedure preserves the contemporaneous correlations among assets, which is essential in portfolio analysis. Following Efron (1979), the bootstrap simulation repeatedly resampled historical observations with replacement.

The probability of selecting each historical observation was adjusted using exponential weighting:

$$p_t = \frac{(1-\lambda)\lambda^{T-t}}{\sum_{j=1}^{T}(1-\lambda)\lambda^{T-j}} \tag{16}$$

where $\lambda = 0.94$. This specification follows the J.P. Morgan/Reuters (1996) technical document. More recent observations therefore receive greater weight than older observations. For the 10-year investment horizon, returns were simulated over 520 weeks using 1,000 simulations for each of the nine assets, together with the ACWI benchmark. For the 20-year horizon, returns were simulated over 1,040 weeks, with the first 520 weeks identical across the two horizons. Historical data were obtained from Yahoo Finance and Federal Reserve Economic Data (FRED) for the period from 1 January 2009 to 31 December 2025.

3 RESULTS AND DISCUSSION

3.1 Descriptive Analysis of the Input Assets

The analysed dataset contained 887 weekly observations covering the period from 9 January 2009 to 31 December 2025. The assets differed substantially in their return and risk profiles. SPY achieved the highest compound annual growth rate (14.45%), followed by IJR (11.92%) and VNQ (9.86%). The ACWI benchmark recorded a CAGR of 11.07%. At the opposite end were long-term U.S. Treasury bonds (TLT), with a CAGR of 1.22%, and the money-market instrument BIL, with a CAGR of 1.18%.

Table 2: Descriptive statistics for the input assets and benchmark, 2009–20252

Panel A: Return and risk							
ETF	**Average annual return**	**CAGR**	**Cumulative return**	**Annualized volatility**	**Maximum drawdown**	**Sharpe**	**Sortino**
SPY	14.95 %	14.45 %	900.37 %	16.87 %	31.83 %	0.810	1.186
IJR	13.71 %	11.92 %	582.77 %	22.07 %	43.60 %	0.563	0.827
VGK	10.01 %	8.26 %	287.22 %	20.26 %	36.58 %	0.430	0.612
EEM	8.56 %	6.64 %	199.17 %	20.64 %	39.16 %	0.352	0.512
LQD	4.65 %	4.37 %	107.37 %	8.67 %	24.68 %	0.388	0.555
TLT	2.24 %	1.22 %	23.05 %	14.32 %	47.83 %	0.067	0.093
BIL	1.17 %	1.18 %	22.16 %	0.29 %	0.44 %	−0.387	−0.943
GLD	10.15 %	9.35 %	359.60 %	15.49 %	44.74 %	0.572	0.850
VNQ	12.21 %	9.86 %	397.56 %	23.67 %	40.07 %	0.462	0.688
ACWI benchmark	11.99 %	11.07 %	499.86 %	17.17 %	32.08 %	0.624	0.900

Panel B: Characteristics of weekly returns							
ETF	**Minimum return**	**Maximum return**	**VaR 95 %**	**ES 95 %**	**Positive weeks**	**Negative weeks**	**Zero-return weeks**
SPY	−14.55 %	12.09 %	3.61 %	5.44 %	520	367	0
IJR	−16.64 %	19.67 %	4.46 %	6.94 %	492	391	4
VGK	−16.00 %	14.20 %	4.00 %	6.59 %	502	382	3
EEM	−13.23 %	10.71 %	4.30 %	6.20 %	476	404	7
LQD	−13.25 %	14.70 %	1.57 %	2.54 %	522	364	1
TLT	−7.69 %	7.65 %	3.32 %	4.41 %	470	415	2
BIL	−0.16 %	0.17 %	0.02 %	0.04 %	476	163	248
GLD	−9.22 %	8.66 %	3.31 %	4.58 %	482	405	0
VNQ	−24.91 %	22.28 %	4.46 %	7.22 %	491	392	4
ACWI benchmark	−13.61 %	11.52 %	3.80 %	5.59 %	512	372	3

Source: Authors' calculations based on Yahoo Finance and FRED data (2026).

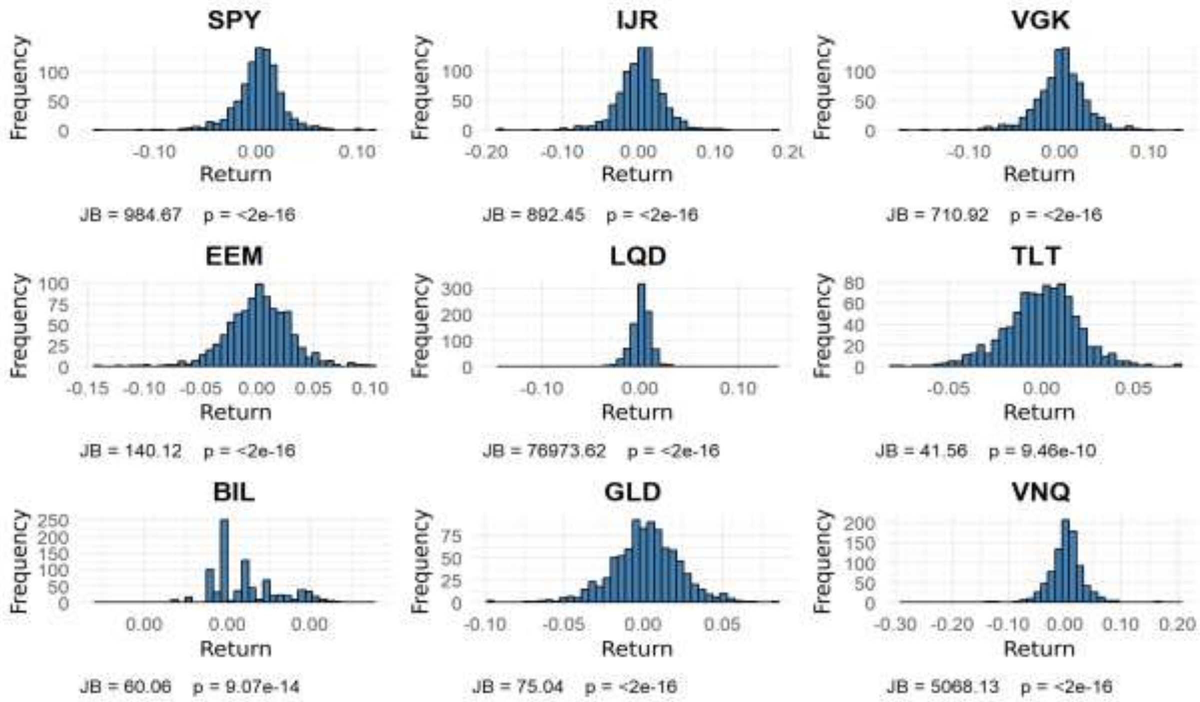

Figure 1: Distribution of historical returns for individual assets1
Source: Authors' calculations based on Yahoo Finance and FRED data (2026).

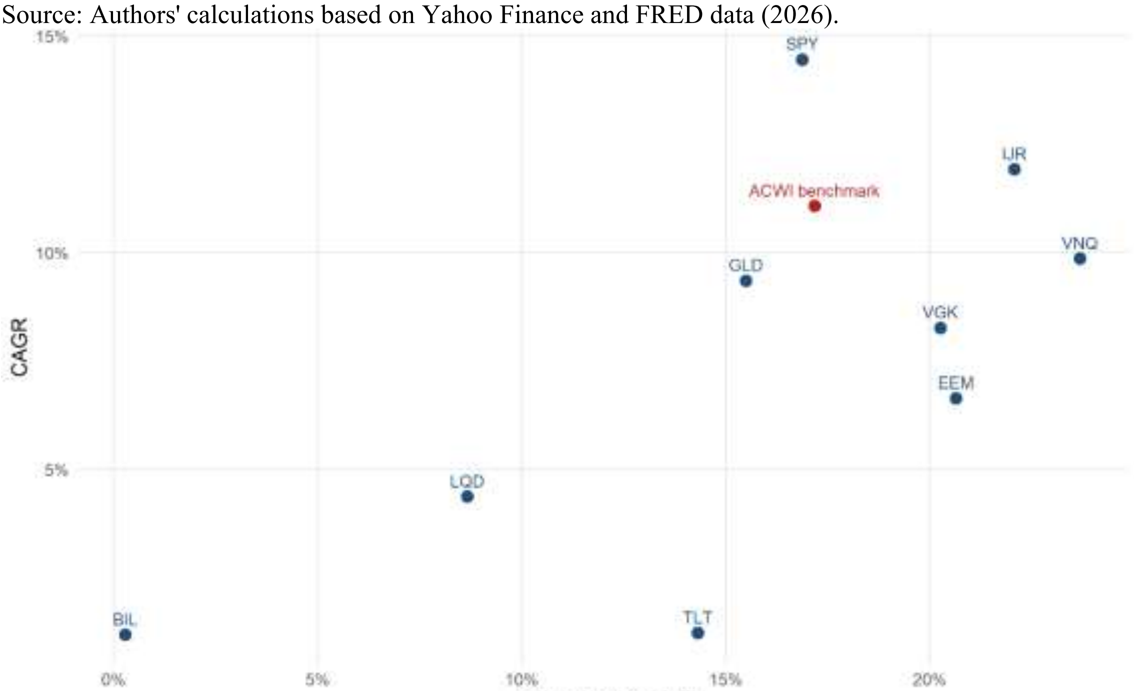

Figure 2: Historical risk–return relationship of portfolio assets2
Source: Authors' calculations based on Yahoo Finance and FRED data (2026).

VNQ exhibited the highest volatility (23.67%), followed by IJR (22.07%), whereas BIL was the least volatile component of the portfolio. Low volatility, however, did not automatically imply favourable risk-adjusted performance. BIL's negative Sharpe ratio indicates that its return did not cover the risk-free rate used in the calculation. TLT's substantial maximum drawdown of 47.83% further demonstrates that even long-term government bonds cannot be regarded as a risk-free asset over the entire sample period.

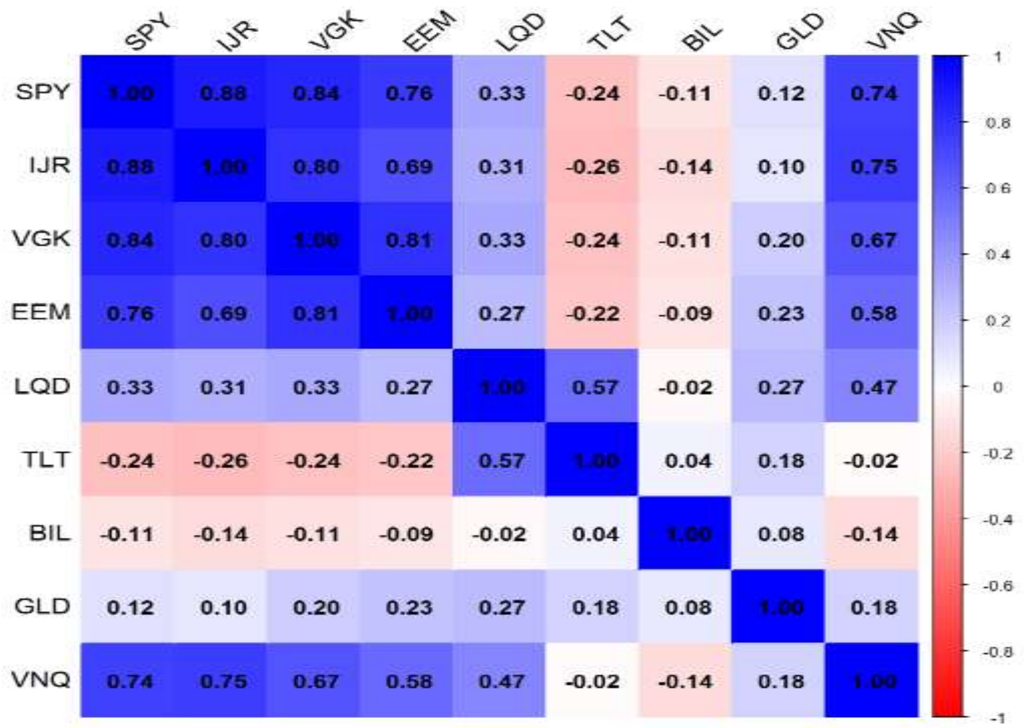

Figure 3: Correlation matrix of the selected funds3
Source: Authors' calculations based on Yahoo Finance and FRED data (2026).

The correlation matrix confirmed strong co-movement among equity markets. The correlation between SPY and IJR was 0.879, that between SPY and VGK was 0.845, and that between VGK and EEM was 0.808. TLT and BIL provided the greatest diversification benefits. The correlations between TLT and the equity ETFs ranged from −0.216 to −0.266. The results therefore support the portfolio perspective according to which an asset's contribution depends not only on its standalone performance, but also on its relationship with the other portfolio components (Markowitz, 1952; Koumou, 2020).

3.2 Historical Backtesting Results

The historical portfolio backtest covered the period from 8 January 2010 to 31 December 2025. The shorter period relative to the input dataset resulted from using the first 52 weeks to estimate the parameters of the dynamic strategies. The ACWI benchmark achieved the highest return, with a CAGR of 10.02%. This return was accompanied by the highest volatility (16.37%), a maximum drawdown of 32.08%, and a weekly ES of 5.39%.

Table 3: Historical backtesting results for the portfolio strategies3

Strategy	CAGR	Cumulative return	Annualized volatility	Maximum drawdown	ES 95 %	Sharpe	Sortino
1/N	7.34 %	211.71 %	10.22 %	22.74 %	3.17 %	0.611	0.880
60/40	7.92 %	240.28 %	11.95 %	24.70 %	3.76 %	0.585	0.837
MW+R	7.62 %	225.42 %	10.48 %	23.61 %	3.31 %	0.624	0.899
SD	8.41 %	265.57 %	12.80 %	25.71 %	4.04 %	0.589	0.849
ACWI benchmark	10.02 %	363.12 %	16.37 %	32.08 %	5.39 %	0.583	0.829

Source: Authors' calculations based on Yahoo Finance and FRED data (2026).

Among the four portfolio strategies, the SD portfolio achieved the highest CAGR (8.41%). Its higher return was, however, accompanied by volatility of 12.80% and a maximum drawdown of 25.71%. MW+R delivered a lower CAGR of 7.62%, but the highest Sharpe ratio (0.624) and Sortino ratio (0.899). The 1/N strategy recorded the lowest volatility and maximum drawdown, while its risk-adjusted performance was only slightly below that of MW+R. The results therefore do not identify a single strategy that dominates across all indicators. SD maximized historical return, MW+R offered the most favourable risk–return trade-off, and 1/N provided comparable stability without requiring optimization. This is consistent with DeMiguel et al. (2009), who found that a simple equal-weight allocation can remain competitive with estimation-intensive models. None of the four strategies generated a negative cumulative return in any of the 316 overlapping ten-year historical windows. The lowest observed CAGR was 3.84% for MW+R, 4.15% for 1/N, 4.63% for 60/40, and 5.01% for SD. This finding highlights the importance of the investment horizon, but it cannot be generalized beyond the analysed period, which was largely characterized by growth in the U.S. equity market.

3.3 Baseline Monte Carlo Simulation Results

The baseline simulation employed an exponentially weighted multivariate bootstrap with $\lambda = 0.94$. Over the ten-year horizon, the SD portfolio achieved the highest median CAGR (22.67%), followed by the ACWI benchmark (21.35%) and MW+R (21.01%). MW+R nevertheless exhibited substantially lower risk than both SD and ACWI. Its median maximum drawdown was 7.81%, and its Sharpe ratio was 1.899.

Table 4: Baseline Monte Carlo simulation results[4]

Panel A: Ten-year investment horizon					
Metric	**1/N**	**60/40**	**MW+R**	**SD**	**ACWI**
CAGR	17.26 *(12.10–22.24)*	18.63 *(12.67–24.53)*	21.01 *(15.34–26.44)*	22.67 *(15.95–29.22)*	21.35 *(13.85–29.22)*
Cumulative return	391.45 *(213.28–645.20)*	451.84 *(229.57–797.25)*	573.54 *(316.76–944.07)*	671.82 *(339.28–1,198.12)*	592.23 *(266.03–1,197.59)*
Annualized volatility	8.20 *(7.75–8.61)*	9.38 *(8.83–9.94)*	8.24 (7.79–8.69)	10.25 *(9.66–10.86)*	12.50 *(11.54–13.65)*
Maximum drawdown	8.53 *(5.95–13.17)*	10.34 *(7.06–16.06)*	7.81 *(5.45–11.71)*	10.63 *(7.25–16.37)*	15.64 *(10.50–24.35)*
ES 95 %	1.82 *(1.57–2.17)*	2.40 *(2.06–2.83)*	1.81 *(1.54–2.14)*	2.34 *(2.00–2.79)*	3.16 *(2.61–3.97)*
Sharpe ratio	1.522 *(0.962–2.077)*	1.470 *(0.907–2.016)*	1.899 *(1.315–2.436)*	1.676 *(1.102–2.241)*	1.304 *(0.788–1.883)*
Sortino ratio	2.512 *(1.472–3.711)*	2.357 *(1.355–3.506)*	3.269 *(2.117–4.520)*	2.788 *(1.691–4.024)*	2.025 *(1.119–3.207)*

Panel B: Twenty-year investment horizon					
Metric	**1/N**	**60/40**	**MW+R**	**SD**	**ACWI**
CAGR	17.28 *(13.76–20.72)*	18.66 *(14.66–22.58)*	20.86 *(16.96–24.76)*	22.80 *(18.23–27.34)*	21.29 *(16.11–26.73)*
Cumulative return	2,323.11 *(1,216.79–4,220.38)*	2,960.65 *(1,441.48–5,768.83)*	4,321.72 *(2,194.64–8,245.67)*	5,979.38 *(2,747.68–12,460.53)*	4,650.35 *(1,882.77–11,318.36)*
Annualized volatility	8.19 *(7.90–8.50)*	9.36 *(8.98–9.77)*	8.22 *(7.92–8.53)*	10.24 *(9.84–10.68)*	12.53 *(11.88–13.28)*

Maximum drawdown	9.78 *(7.06–14.81)*	11.97 *(8.71–17.69)*	8.93 *(6.54–13.32)*	12.14 *(8.85–18.37)*	18.14 *(12.98–26.88)*
ES 95 %	1.83 *(1.64–2.06)*	2.42 *(2.17–2.70)*	1.82 *(1.63–2.04)*	2.35 *(2.11–2.65)*	3.23 *(2.71–3.75)*
Sharpe ratio	1.519 *(1.144–1.879)*	1.465 *(1.098–1.836)*	1.884 *(1.496–2.264)*	1.680 *(1.303–2.054)*	1.297 *(0.939–1.675)*
Sortino ratio	2.514 *(1.812–3.289)*	2.337 *(1.683–3.098)*	3.232 *(2.474–4.087)*	2.778 *(2.059–3.596)*	1.997 *(1.368–2.733)*

Source: Authors' calculations based on 1,000 Monte Carlo simulations and Yahoo Finance and FRED data (2026).

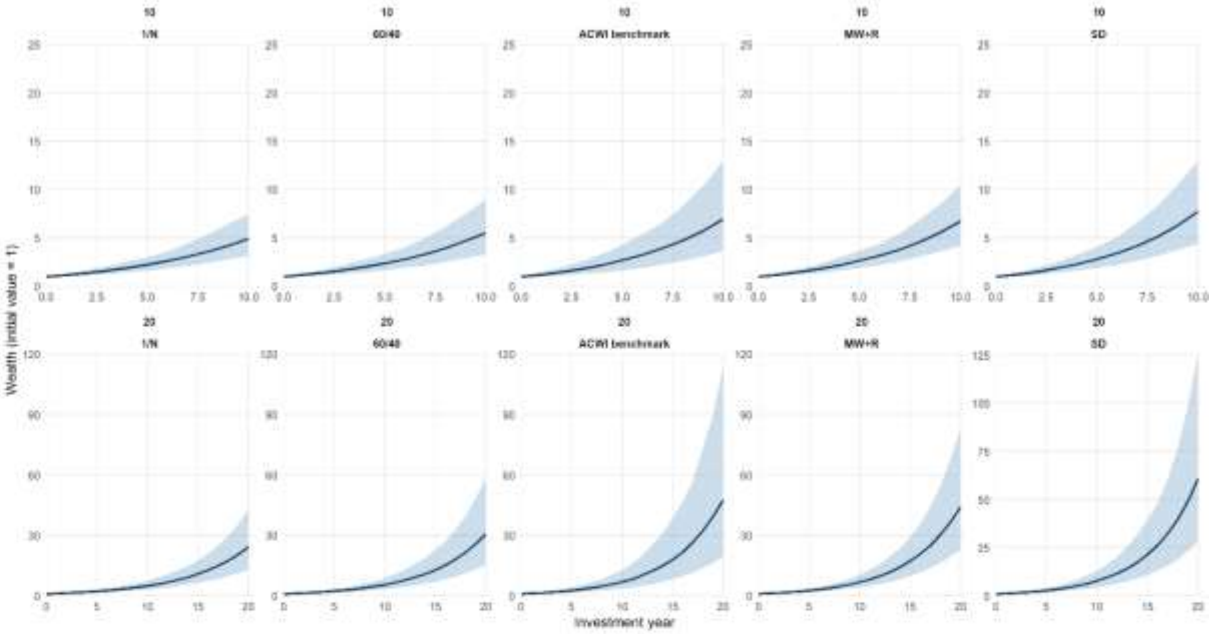

Figure 4: Simulated portfolio wealth paths—median and 5th–95th percentiles4
Source: Authors' calculations based on 1,000 Monte Carlo simulations (2026).

At the twenty-year horizon, the ordering of the strategies by median CAGR remained almost unchanged. The percentile range of CAGR narrowed, although the range of terminal portfolio values widened substantially because of compounding. Extending the horizon also increased maximum drawdowns slightly, since a longer path provides more opportunities for an adverse market episode to occur.

The absolute values in the baseline scenario should be interpreted with caution. The EWMA bootstrap with $\lambda = 0.94$ assigns substantially greater weight to more recent observations; consequently, the results primarily reflect the return environment at the end of the sample period. This construction also explains why the simulated median CAGRs (approximately 17–23%) lie far above the historical backtest CAGRs of roughly 7–8% reported in Table 3: with $\lambda = 0.94$ applied to weekly data, resampling is dominated by the most recent, unusually strong phase of the market, whereas the backtest averages over the entire 2010–2025 period, including its weaker episodes. The simulated CAGRs should therefore not be interpreted as forecasts of future returns. More informative are the relative ranking of the strategies and its stability under alternative simulation assumptions.

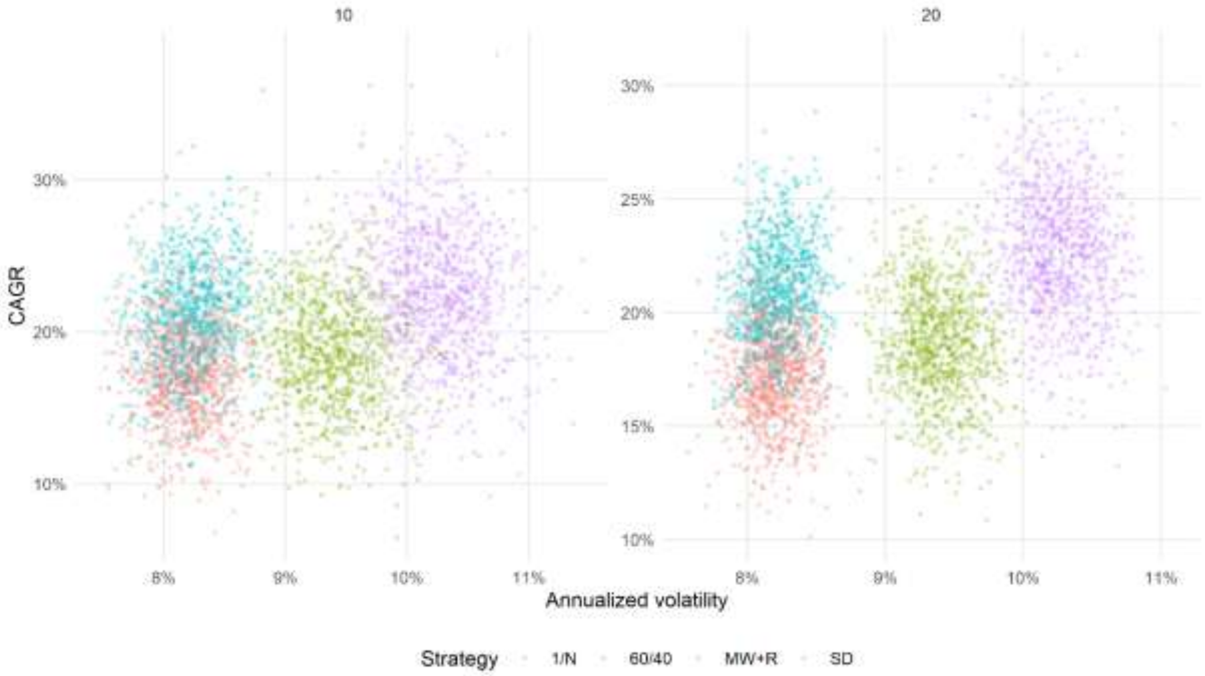

Figure 5: Distribution of risk and return across 1,000 simulations5
Source: Authors' calculations based on 1,000 Monte Carlo simulations (2026).

3.4 Robustness of the Results and Strategy Correlation Matrix

The stability of the results was examined across four simulation scenarios that differ in how historical weekly observations are resampled: (i) the baseline exponentially weighted bootstrap with λ = 0.94; (ii) an exponentially weighted bootstrap with a slower decay factor (λ = 0.97), which reduces the emphasis on the most recent observations; (iii) an unweighted i.i.d. bootstrap, in which all historical weeks are drawn with equal probability; and (iv) a moving-block bootstrap with fixed blocks of 13 consecutive weeks (Künsch, 1989), which preserves short-term dependence and volatility clustering in returns. Each scenario was simulated with 1,000 paths at both horizons. The robustness analysis confirmed that the absolute level of simulated returns is sensitive to the method used to sample historical observations. Under the unweighted bootstrap, median CAGRs ranged from approximately 8% to 9.5%, whereas the exponentially weighted scenarios produced higher values. The relative evaluation of the strategies was nevertheless more stable.

Table 5: Stability of the composite strategy ranking across four simulation scenarios5

Horizon	Strategy	Mean rank	Rank SD	Best–worst rank	Share ranked first	Median CAGR	Median Sharpe ratio	Median MDD
10 years	1/N	2.25	0.96	1–3	25.00 %	12.73 %	1.050	13.92 %
10 years	60/40	3.50	0.58	3–4	0.00 %	13.70 %	1.006	16.74 %
10 years	MW+R	1.00	0.00	1–1	100.00 %	14.26 %	1.206	13.28 %
10 years	SD	2.75	0.96	2–4	0.00 %	15.36 %	1.081	17.58 %
20 years	1/N	2.25	0.96	1–3	25.00 %	12.90 %	1.060	16.76 %
20 years	60/40	3.50	0.58	3–4	0.00 %	13.89 %	1.006	20.01 %
20 years	MW+R	1.00	0.00	1–1	100.00 %	14.42 %	1.218	15.72 %
20 years	SD	2.75	0.96	2–4	0.00 %	15.48 %	1.081	20.77 %

Source: Authors' calculations based on four simulation scenarios (2026).

MW+R ranked first at both horizons in the moving-block bootstrap scenario (Künsch, 1989), jointly with 1/N. Its advantage was not the highest return in isolation, but the combination of a high Sharpe ratio, a low maximum drawdown, and favourable ES. SD achieved the highest CAGR, but its greater exposure to volatile assets resulted in weaker downside-risk metrics. The traditional 60/40 portfolio generally ranked third or fourth in the composite assessment.

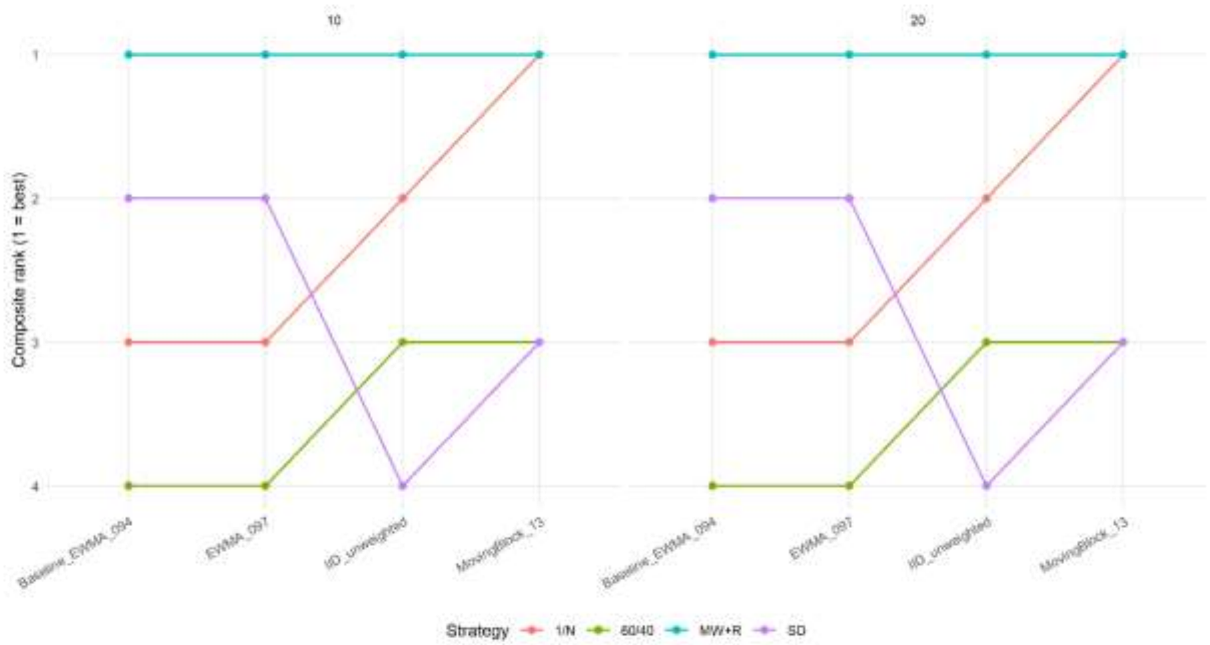

Figure 6: Robustness of strategy rankings under alternative simulation assumptions6
Source: Authors' calculations (2026).

The results support the view that robustness should not be equated solely with the highest return. While SD is better suited to an investor who prioritizes growth in terminal wealth, MW+R provided the best risk–return trade-off. The 1/N strategy remains a relevant alternative because of its simplicity and stability, particularly for investors unwilling to bear the model and estimation risk associated with optimization.

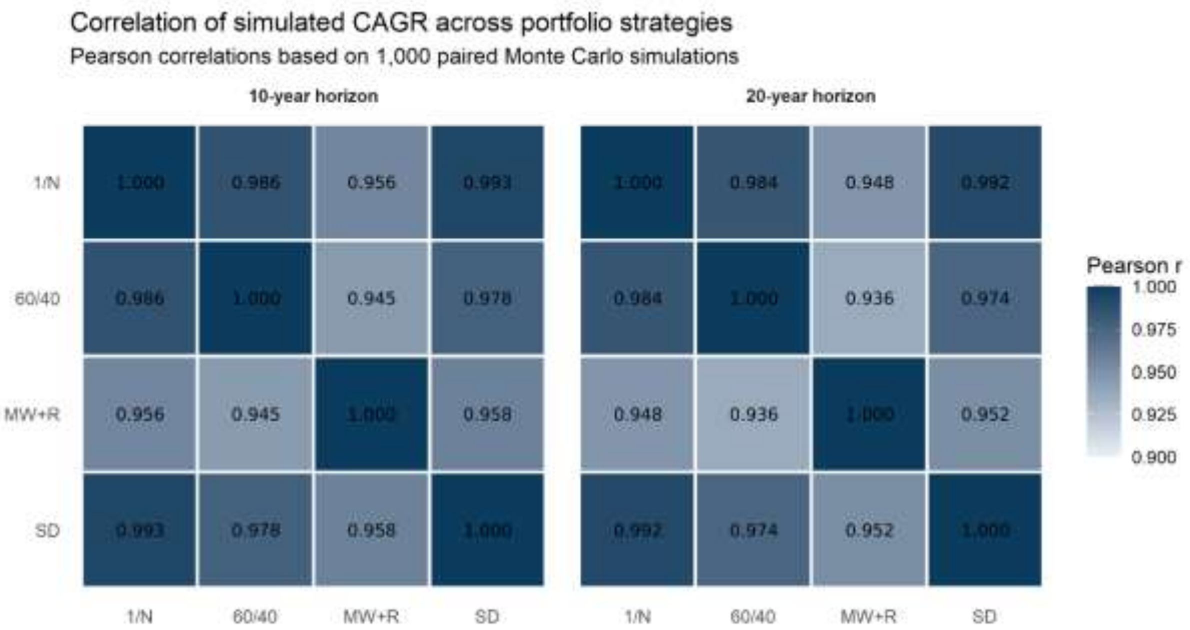

Figure 7: Correlations of strategy CAGRs over 10- and 20-year investment horizons7

Source: Authors' calculations based on 1,000 paired Monte Carlo simulations (2026).

CAGR correlations were very high at both horizons. They ranged from 0.945 to 0.993 over the ten-year horizon and from 0.936 to 0.992 over the twenty-year horizon. The highest correlation was observed between 1/N and SD, whereas the lowest was between MW+R and 60/40. The shared simulated market path therefore explains a substantial proportion of the variability in the outcomes of all strategies. The differences among them arise mainly in the level of return achieved, volatility, and downside protection, rather than in entirely different directions of performance.

CONCLUSION

This paper assessed the robustness of four asset allocation strategies—1/N, 60/40, MW+R, and SD—over 10- and 20-year investment horizons. The analysis combined historical backtesting of weekly data for nine ETFs over the period 2009–2025 with Monte Carlo simulations based on an exponentially weighted multivariate bootstrap and sensitivity testing under alternative simulation assumptions. This design made it possible to evaluate the strategies not only over a single realized historical period, but also across the full distribution of possible outcomes.

The historical backtest did not identify a strategy that dominated across all indicators. Among the portfolios under comparison, SD achieved the highest return, with a CAGR of 8.41%, but also the highest volatility (12.80%) and deepest maximum drawdown (25.71%). MW+R recorded a lower CAGR of 7.62%, but the most favourable risk-adjusted performance, with a Sharpe ratio of 0.624 and a Sortino ratio of 0.899. The equally weighted 1/N portfolio exhibited both the lowest volatility and the lowest maximum drawdown, while delivering only slightly weaker risk-adjusted performance. It therefore confirmed the competitiveness of simple naive diversification relative to estimation-intensive models (DeMiguel et al., 2009). An important finding is that none of the strategies generated a negative cumulative return in any of the 316 overlapping ten-year windows, illustrating the stabilizing effect of a long investment horizon. The Monte Carlo simulations confirmed and refined these conclusions. At both horizons, SD achieved the highest median simulated CAGR (22.67% over 10 years and 22.80% over 20 years), but its greater exposure to volatile assets produced the least favourable downside-risk metrics among the diversified strategies under comparison. By contrast, MW+R ranked first in the composite robustness assessment in all four simulation scenarios and at both horizons, combining a high Sharpe ratio, the lowest maximum drawdown, and favourable Expected Shortfall. The traditional 60/40 portfolio generally occupied the lowest positions in the composite ranking. Extending the horizon from 10 to 20 years narrowed the range of simulated CAGRs, but compounding simultaneously widened the range of terminal portfolio values and slightly deepened maximum drawdowns.

The findings indicate that strategy robustness cannot be equated with return maximization. Markowitz optimization supplemented by a maximum asset-weight constraint, a prohibition on short selling, and regular rebalancing provided the best risk–return trade-off, and its relative ranking remained stable when the simulation assumptions were varied. SD is more appropriate for an investor who prioritizes terminal wealth growth and has a higher risk tolerance, whereas 1/N represents a relevant alternative for investors unwilling to bear the model and estimation risk of optimization. A practical implication for strategic asset allocation is that a disciplined, diversified allocation with controls on risk concentration delivered a more favourable risk–return relationship than the global equity benchmark alone, both during the analysed period and in the simulated scenarios. The results are subject to several limitations. Much of the sample period (2009–2025) was characterized by a predominantly rising U.S. equity market, so the conclusions partly reflect conditions favourable to equity-oriented allocations; in a prolonged bear market or a stagnating market regime, the relative attractiveness of the strategies—particularly of the return-seeking SD portfolio—could differ. Exponential weighting further emphasizes the return environment at the end of the period. The analysis also abstracts from transaction costs, taxes, and currency hedging; in this respect, the dynamic SD and MW+R strategies are likely to require higher portfolio turnover, and therefore higher trading costs, than the static 1/N and 60/40 rules, which would reduce their net performance in practice. The absolute levels of simulated returns should therefore not be interpreted as forecasts of future performance. Further research could incorporate transaction costs, alternative rebalancing frequencies and rules, models that account for changes in market regimes, and a broader set of strategies including risk-parity and minimum-variance approaches. Risk-parity strategies, which equalize the risk contributions of the individual assets, would provide a natural counterpart to the volatility-proportional SD portfolio, while minimum-variance portfolios, which require no expected-return estimates, would allow the robustness framework to be applied to an optimization rule designed purely for risk control. Such extensions would permit a more comprehensive assessment of the generalizability of the findings.

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