

MIMS – Long-Short Equity Fund

Portfolio Management Team

Report – December 2025

Fund Description

MIMS – Long Short Equity Fund is a semi-automated actively-managed fund by Minerva Investment Management Society, based on a zero-net investment 'multi-factor' strategy. The Fund has the investment objective of achieving a positive absolute return throughout all market conditions, maintaining a constant euro and geographical exposure at each rebalancing.

Market Update

- In the US, the economy entered a new phase of disinflation and policy easing following the Federal Reserve's September rate cut, the first since 2020, lowering the target range to 4.00-4.25%. Growth remained resilient, with GDP expanding around 2–2.5% annualized in Q3, supported by strong consumer spending and moderating inflation (core PCE near 3% YoY). Markets responded positively to this dovish pivot: the S&P 500 gained 8.1%, and the Nasdaq rallied 11.2%, reaching new highs driven by technology and AI-related optimism. However, valuations reached historically stretched levels, with the Shiller P/E around 40× and the Buffett Indicator at 221%, signaling elevated investor exuberance. Despite strong equity performance, volatility spiked briefly in early October amid geopolitical concerns, highlighting fragile confidence at stretched price levels.
- In the EU, economic momentum remained subdued. GDP rose only 0.2% QoQ, yet easing inflation (headline 2.2%) and a stable ECB policy rate of 2.00% offered moderate relief. The euro appreciated toward 1.10 USD as the transatlantic rate gap narrowed, though sluggish industrial production and weak exports persisted.
- Meanwhile, China recorded 4.8% YoY growth, slower than in prior quarters, prompting Beijing to intensify fiscal and monetary support, including a ¥5 trillion bond issuance to bolster infrastructure and local governments. These measures fueled a 19% surge in Chinese equities and a broader 10% rebound in emerging markets. Overall, global markets faced diverging paths: U.S. optimism anchored by policy easing and corporate earnings, Europe weighed by stagnant growth, and China stabilizing via aggressive stimulus.
- Investor sentiment remained cautiously constructive, though rising valuations and geopolitical uncertainty leave limited room for policy missteps.



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Factor Investing Strategy

VALUE	MOMENTUM
QUALITY	LOW VOLATILITY
ILLIQUIDITY	YIELD CURVE

3 Steps Investment Approach

Multi Factor Analysis

Fundamental metrics are identified that best proxy each of the 5 factors on which the investment style is grounded. The process involves theoretical-based frameworks as well as empirical evaluations. Cross-team expertise and Minerva IMS insights are deployed.

Screening and Normalization

Stocks are evaluated on the basis of their exposure to each single factor. Outliers are substituted through a Winsorization procedure for every factor. The output of the process is a synthetic score, which is then used to rank all the stocks.

Strategic Asset Allocation

Portfolio allocation comes to live. Based on the ranking produced, long and short positions are taken accordingly. Usually, no intermediate rebalancing is performed. Significant changes may lead to reconsider the chosen set of factors, or their weights, thus affecting the first step of the process.

Investment Approach

The Fund uses a multi-factor based investment style adopting a quantitative proprietary model in order to achieve a systematic rule-based approach to stock selection. Stocks are selected from the broad US Equity market (S&P 500 index) and the European Equity market (STOXX EUROPE 600 index).

This semester, the fund continued the period of major transition started the previous year. The model is now completely Python-based: The composition of the factors and consequently our investment strategies are possible throughout the time-series approach we developed. The crude baseline model continue to use sector-specific winsorization and now implements a new version of a quality factor and introduces a yield curve factor.

The model is based on a six-factor model, seeking to extract the risk premia coming from the size factor (Illiquidity, Amihud (2002)), value factor (HML, Fama & French (1992)), quality (QLT), momentum (MOM, Carhart (1997)), idiosyncratic volatility (IVOL, Ang, Hodrick, Xing, and Zhang (2006)) and yield curve factor ((Beta0, BETA1, BETA2), Nelson and Siegel (1987)). Explanations of each factor can be found under "Fund Factors".

5 factors are constructed by ranking assets based on a specific metric (e.g. book-to-market ratio) that is presumed to reflect the factor of interest. After ranking, the assets are grouped into portfolios. In this fund, decile portfolios are used. At each time interval (in this case, monthly), the assets are re-ranked and reassigned to the appropriate portfolios. Yield curve factor is constructed by extracting Beta1 coefficients from Nelson-Siegel Model.

Following a style-analysis approach, we regress each stock in our investable universe on our 6 factors to derive the corresponding factor coefficients. These coefficients are then globally standardized and winsorized per sector to get the final z-scores for each factor, representing a company's exposure to that factor. Once exposures are obtained, a weighted average final score is calculated for each company using our discretionary weights (outlined under "Factor Weights"). Companies are then ranked based on these final scores.

Winsorization is performed in order to isolate and substitute the most extreme observations with reference to each single factor, considering the average value and the standard deviation of the characteristic in analysis for every sector.

After constructing the initial portfolio, qualitative checks are conducted to ensure sector neutrality and geographic balance. This is achieved by substituting companies from overrepresented sectors by those ranked next from underrepresented sectors. The final portfolio consists of 20 stocks in each segment (long/short, EU/US). The weights of the selected stocks are then optimized using mean-variance approach such that the weights in the long leg sum to 1 and those in the short leg also sum to 1. This procedure is further discussed in the "Improving factor weightings" section. Consequently, the overall portfolio weight sums to zero. The above-mentioned mechanism enables the fund to take more significant positions in companies with higher returns and lower volatility.

Fund Factors

Value Factor – Long position

- This semester we built our own Value factor instead of using the Fama-French HML series. It's based on a simple book-to-market ratio (B/M), calculated from company fundamentals. Each month, stocks are split by market capitalization (Small vs Big) and ranked by their book-to-market values.

Momentum Factor – Long position

- MOM: following the evidence provided by Jegadeesh and Titman (1993), Asness (1994) and Carhart (1997), we consider momentum defined as the sum of the 12 monthly returns preceding the last one divided by 11, as a buy signal. We assume, as a practical heuristic, that stocks with a positive average return over recent months will continue to perform well in the near future.

Quality Factor – Long position

- Return on Equity (ROE): we consider a high ROE as a signal of high profitability and thus a buy signal. Specifically, we are assuming that company's profitability will stay stable in the future and will be a reliable driver of increases in prices.
- 5y growth in ROE: to account for the growth, we assess the earnings increase over the last five years relative to the equity's book value from five years ago. This allows us to reward companies that showed an increase in profitability while smoothing earnings by considering a 5-year window.
- Debt-to-Equity (D/E): for the safety dimension of our quality factor we consider the D/E ratio. A high D/E ratio indicates an excessive level of debt for the firm, representing a risk and also inflating ROE when earnings are positive.
- Payback Period (Total Liabilities/CFO): Measures the time a company takes to generate enough cash flow to repay its debt, with shorter periods indicating stronger stability.
- Earnings Volatility (EVOL): reflects fluctuations in quarterly ROE, with lower volatility displaying consistent performance.

Low Volatility Factor – Long position

- Standard deviation: we deem a higher standard deviation to be a selling signal, since it reveals a riskier situation where returns are less stable, and, consequently, less predictable Ang, Hodrick, Xing, and Zhang (2006).

Yield Curve Factor– Long position

- The Nelson–Siegel model decomposes the yield curve into three key factors: β_0 (level), capturing parallel shifts in long-term rates; β_1 (slope), reflecting steepening or flattening driven by monetary-policy expectations; and β_2 (curvature), measuring movements in the mid-term segment of the curve. These factors reveal how stocks react to structural changes across the term structure

Illiquidity Factor – Long position

- Based on Amihud (2002), calculated as the average of the absolute daily return divided by trading volume in value terms. It captures the price impact per unit of volume, where higher values imply less liquidity and greater trading costs.
- Each month, stocks are ranked by their Amihud measure; we go long the most illiquid decile and short the most liquid decile.

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US: Tactical Decisions

The U.S. factor allocation has been repositioned to reflect a macroeconomic environment defined by decelerating but still above-target services inflation, a labour market that remains resilient, and a Federal Reserve that continues to telegraph a higher-for-longer policy stance, despite further interest rates cuts are expected by the first quarter of 2026. With long-dated yields rising and the Treasury curve steepening from historically inverted levels, investor positioning remains highly sensitive to rate-path guidance, commanding a defensive factor construction.

The inverted Size exposure (10%) captures the ongoing stress among smaller firms, many of which are now confronting a significantly higher refinancing wall as pandemic-era low-coupon debt matures. Rising credit spreads and a decline in small-business optimism reinforce the view that balance-sheet fragility is a key vulnerability for this segment. Value holds a 15% allocation, supported by persistent valuation dispersion and the relative insulation of value-oriented sectors from duration shocks. Momentum remains at 10%, acknowledging the recent loss of directional conviction across U.S. equities as mega-cap leadership narrows and short-term factor reversals intensify. Quality, at 20%, remains a central pillar of the U.S. configuration. Low Volatility retains a 25% weight, offering protection against macro-driven volatility spikes tied to uncertainty around the Fed's timing of eventual easing. At the curve level, BETA0 is held at -10% to hedge against parallel upward shifts in yields, while BETA1 and BETA2, both at 5%, position the portfolio to benefit from continued steepening and curvature normalisation following the long 2022–2024 inversion.

Overall, the U.S. positioning reflects a climate where inflation remains sticky, rate uncertainty still anchors risk sentiment, and factor robustness, particularly profitability and balance-sheet quality, continues to command a premium.

EU: Tactical Decisions

The European allocation has been adjusted to reflect a macroeconomic outlook characterised by stagnating growth, weak industrial production, and an ECB navigating the balance between easing financial conditions and containing sticky services inflation.

With Eurozone PMIs oscillating around contractionary territory and credit surveys indicating further tightening in bank lending standards, the Size factor remains inverted at 10%, consistent with the pressures facing smaller European firms. Limited market access, higher bank funding costs, and subdued domestic demand across major economies place these companies at a disadvantage relative to larger, more diversified corporations. Value is held at 10%, indicating a neutral stance in light of persistent valuation attractiveness but ongoing cyclical fragility in value-heavy segments such as industrials and financials. Momentum remains at 10%, reflecting unstable trend profiles within European equities as investor flows whipsaw between defensives and cyclicals in response to shifting macro signals. Quality retains a full 25% allocation.

Low Volatility holds at 25%, serving as a stabilising allocation in an environment prone to idiosyncratic shocks—from energy-market fluctuations to political developments across the bloc. The yield-curve factors remain anchored at -10% for BETA0 and 5% each for BETA1 and BETA2, aligning the portfolio with a European sovereign-curve that has recently exhibited modest steepening as front-end rate cut expectations rise faster than long-term inflation risk premiums decline. Collectively, these adjustments position the EU factor configuration to navigate a landscape defined by weak growth momentum, cautious monetary easing, and the continued premium placed on high-quality, low-volatility equity exposures.

US: Factor Weights

Value (15%)	High-Minus-Low Book-to-Market (HML) Factor	15%
Illiquidity (10%)	Illiquidity Factor, Amihud (2002)	10%
Momentum (10%)	Carhart (1997) Momentum	10%
Quality (20%)	Profitability: ROE	4.8%
	Growth: ROE 5y CAGR	4.4%
	Debt to Equity	3.2%
	Safety: Payback Period	3.2%
	EVOL (ROE Volatility)	4.4%
Low Volatility (25%)	Standard deviation of idiosyncratic errors from factor model	25%
BETA0 (-10%)	Beta ₀ : Level sensitivity of Nelson–Siegel yield curve	-10%
BETA1 (5%)	Beta ₁ : Slope sensitivity (Yield-Curve Steepness)	5%
BETA2 (5%)	Beta ₂ : Curvature sensitivity (new)	5%

EU: Factor Weights

Value (10%)	High-Minus-Low Book-to-Market (HML) Factor	10%
Illiquidity (10%)	Illiquidity Factor, Amihud (2002)	10%
Momentum (10%)	Carhart (1997) Momentum	10%
Quality (25%)	Profitability: ROE	6%
	Growth: ROE 5y growth	5.5%
	Debt to Equity	4%
	Safety Factor: Payback Period	4%
	EVOL (ROE Volatility)	5.5%
Low Volatility (25%)	Standard deviation of idiosyncratic errors from factor model	25%
BETA0 (-10%)	Beta ₀ : Level sensitivity of Nelson–Siegel yield curve	-10%
BETA1 (5%)	Beta ₁ : Slope sensitivity (Yield-Curve Steepness)	5%
BETA2 (5%)	Beta ₂ : Curvature sensitivity (new)	5%

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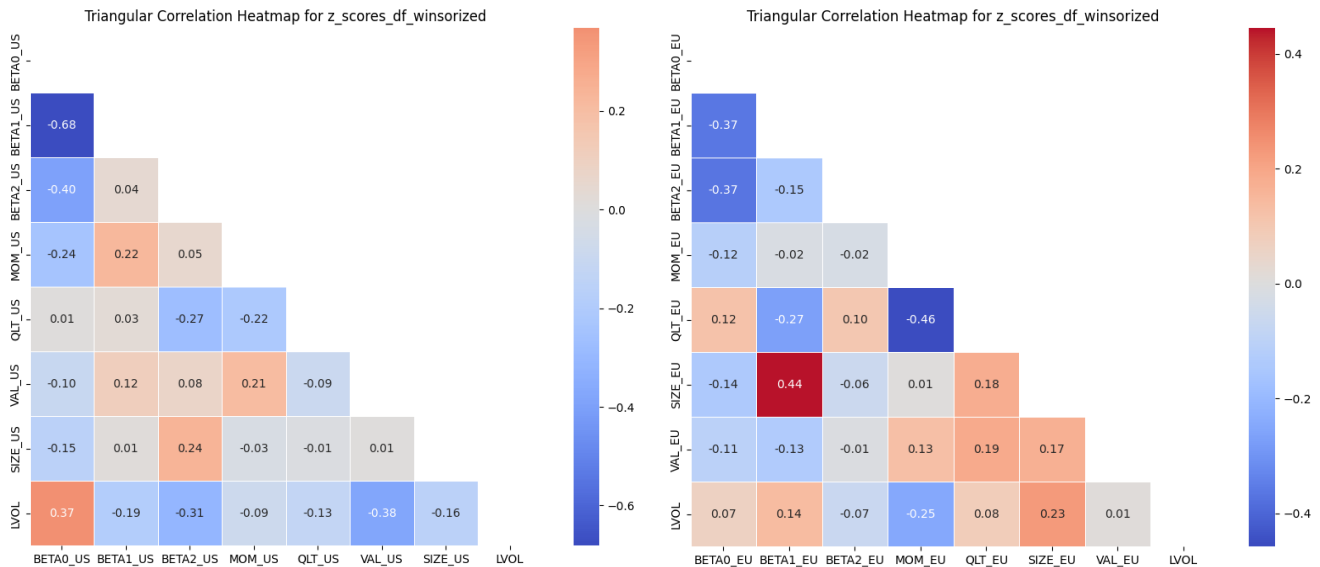
Statistical Metrics & Factor Diagnostics

Cross-Factor Dependence

Pairwise correlations among the eight style factors remain generally low, with only a few values showing extreme correlations up to ± 0.7 .

The strongest positive relationship is observed between Liquidity and Beta 1 in the European leg ($\rho = +0.44$). Beta 0 and Beta 1 in the American leg are the strongest negatively correlated ($\rho = -0.68$), suggesting a pattern of flattening of the yield curve as it shift upwards in level.

Most factors still appear quite uncorrelated with each other, preserving the idea of equal risk contribution.



Distributional Checks & Normality

Descriptive statistics confirm that the factor scores are centred around zero and standardized to unit variance after winsorisation, as intended.

To assess the shape of their distributions, we apply the **Shapiro–Wilk** test (a common normality check that evaluates whether a sample comes from a Gaussian distribution). Results indicate significant departures from normality for all factors ($p < 0.05$) except Low Volatility (LVOL), which appears approximately normal ($p = 0.19$). While this non-normal behaviour is not unusual in financial data, it has implications for risk modeling: in particular, fat-tailed distributions can distort classical covariance estimates.

For this reason, the current framework relies on a winsorised covariance matrix, which mitigates the impact of extreme values and improves robustness.

	SW Statistic	p-value	$\sim \mathcal{N}$
BETA0_US	0.9880	0.0001	No
BETA1_US	0.9819	0.0000	No
BETA2_US	0.9835	0.0000	No
MOM_EU	0.9844	0.0000	No
QLT_EU	0.9783	0.0000	No
ILLIQ_EU	0.9806	0.0000	No
VAL_EU	0.9868	0.0000	No
LVOL	0.9897	0.0004	No

	SW Statistic	p-value	$\sim \mathcal{N}$
BETA0_US	0.9982	0.8888	Yes
BETA1_US	0.9671	0.0000	No
BETA2_US	0.9953	0.1375	Yes
MOM_US	0.9929	0.0174	No
QLT_US	0.9935	0.0296	No
ILLIQ_US	0.9919	0.0080	No
VAL_EU	0.9942	0.0548	Yes
LVOL	0.9973	0.5865	Yes

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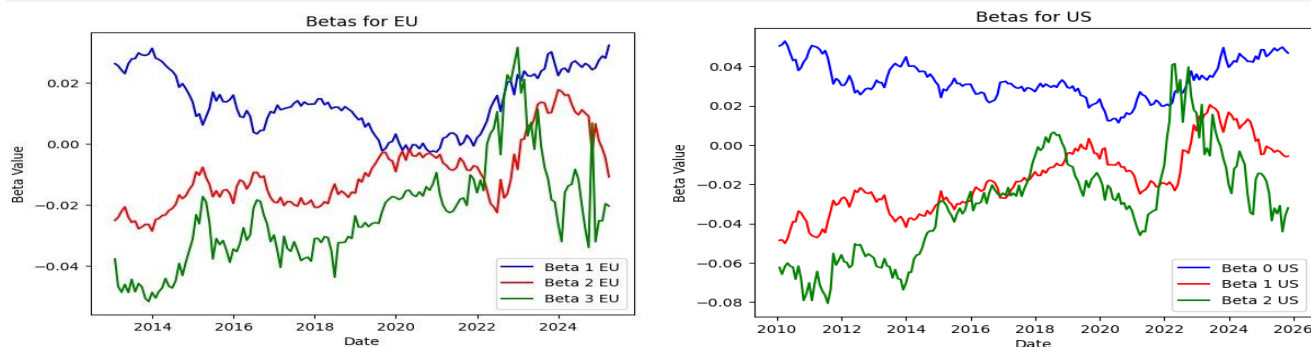
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Yield Curve Factor

Macro-Yield Curve Factor (Nelson-Siegel Betas)

Movements of the yield curve, whether parallel shifts (Level), steepenings (Slope), or changes in curvature, summarize both the stance of monetary policy and expectations on future growth and inflation. Firms with different profiles respond differently to these changes due to various characteristics, such as leverage and discount-rate sensitivity. By quantifying such sensitivities, we can construct a portfolio that systematically earns returns when those macro shocks occur by translating the dynamics of interest rates into cross-sectional equity payoffs.

The Nelson–Siegel model provides a smooth parametric representation of the yield curve using only three parameters: β_0 (Level): parallel shifts of the curve; β_1 (Slope): short vs. long-term spread; β_2 (Curvature): changes in the belly of the curve. This interpolation method fills the gaps by generating a continuous and coherent curve across all maturities. It solves the problem of comparing yield dynamics consistently over time, turning scattered bond data into an analytically tractable structure.



Methodology:

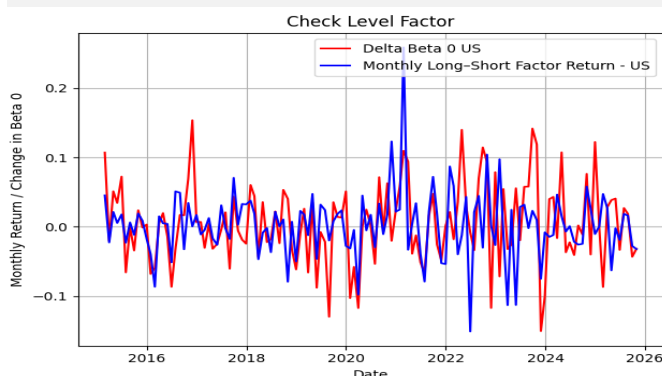
1. Estimate monthly Nelson–Siegel betas (β_0 , β_1 , β_2) for US and EU yield curves using

$$\text{the functional form: } \gamma(\tau) = \beta_0 + \frac{1 - e^{-\lambda\tau}}{\lambda\tau} + \beta_2 \left(\frac{1 - e^{-\lambda\tau}}{-\lambda\tau} \right)$$

2. Compute monthly shocks $\Delta\beta_0$, $\Delta\beta_1$, $\Delta\beta_2$, defined as changes in each factor between consecutive months, capturing yield-curve movements.

3. For each stock, it is computed a rolling 60-month OLS of excess returns on the three factors at the same time, in order to reduce the risk of incorporating variations attributable to others, and hence reducing multicollinearity.

Each coefficient (γ) measures how much a stock reacts to a one-unit shock in that yield-curve component and thanks to these results the long and short legs for each factor can be constructed by taking respectively the deciles with the most positively and negatively sensible stocks for each beta at each point in time: $r_{i,t}^E = d_i + \gamma_i^{(k)} \Delta\beta_{k,t} + \varepsilon_{i,t}$, $k \in \{0,1,2\}$



The final cumulative performance of the Level Factor confirms the macro-consistency of the strategy. The 2020 drawdown reflects the collapse in global yields during the Covid crisis, while the recovery mirrors the normalization of rates through 2025.

The NS Yield Curve Factor captures the equity market's response to yield-curve shifts, turning interest-rate movements into tradable signals.

This approach ensures that the factor's returns are driven by yield-curve movements. By design, long and short legs have equal dollar exposure, making the strategy approximately market-neutral. When the Level factor rises (yields increase), the portfolio gains because it is long in stocks positively exposed to rate shocks and short in those less sensitive. Conversely, during negative yield shocks, shorting the factor generates positive performance. The portfolio was subject to yearly rebalancing, as in classic Fama French factor construction.



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Quality Factor

Building on the findings of Quality Minus Junk (Asness, Frazzini & Pedersen, 2017), we are strengthening the traditional Quality factor by integrating a fifth component, Earnings Volatility (EVOL), and by reallocating weights to emphasize some selected aspects.

EVOL is computed as the standard deviation of quarterly ROE over the most recent sixty observations, providing a straightforward insight on the predictability of a firm's earnings and profitability (Figure 1).

Firms scoring in the lowest decile of EVOL generate extremely stable profits that are hence usually less subject to industry-wide and macroeconomic downturns. Conversely, elevated EVOL indicates an erratic earnings pattern, and in such cases, the stock is systematically penalized in our z-score composite.

By rewarding low-volatility earners, the updated Quality factor can also capture the natural shift toward predictable investment that becomes prominent during macro stress and times of uncertainty.

In the previous framework, each of the four sub-scores (ROE, ROE-growth, Debt-to-Equity, and Safety) carried an equal 25 % weight, a straightforward approach to obtain a diversified exposure to the various sub-factor, but a more tailored approach can be.

The revised approach for this semester retains these four pillars but re-weights them and inserts EVOL as follows: ROE 24 %, ROE-growth 22 %, EVOL 22 %, Debt-to-Equity 16 %, and Safety 16.

This redistribution reflects a broad industry consensus: a survey of leading asset managers (BlackRock, Vanguard and Fidelity among others) shows that profitability and earnings stability consistently outrank raw leverage in contemporary quality screens (Figure 2).

Furthermore, during times of economic uncertainty (as opposed to monetary instability), profitability becomes an even more valuable component within the quality factor. Firms that consistently generate strong profits are more likely to maintain operational resilience, reinvest in growth, and weather downturns without resorting to external financing or cost-cutting that might impair long-term value. High profitability often signals durable competitive advantages, pricing power, and efficient management, offering stability in unpredictable macroeconomic environments.

While leverage and balance sheet strength are crucial, especially during periods of monetary tightening, economic uncertainty calls for a focus on firms that can internally sustain themselves through robust income generation. As such, assigning a greater weight to profitability within the quality composite can enhance a portfolio's defensive profile and return consistency across cycles.

To reflect this priority and to align closer with the industry standard, we have hence slightly adjusted the equal-weighted allocation of the quality subcomponents redistributing weights in favor of those more aligned with profitability as shown earlier.

$$\text{Earnings Volatility} = \sqrt{\frac{1}{20} \sum_{i=1}^{20} (ROE_i - \overline{ROE})^2}$$

FIGURE 1: Earning Volatility Formula

Source:

EVOL (Earnings Volatility) is the standard deviation of ROE calculated over a 20 quarters (5-year) basis. It aims to capture the stability and predictability of profitability over time.

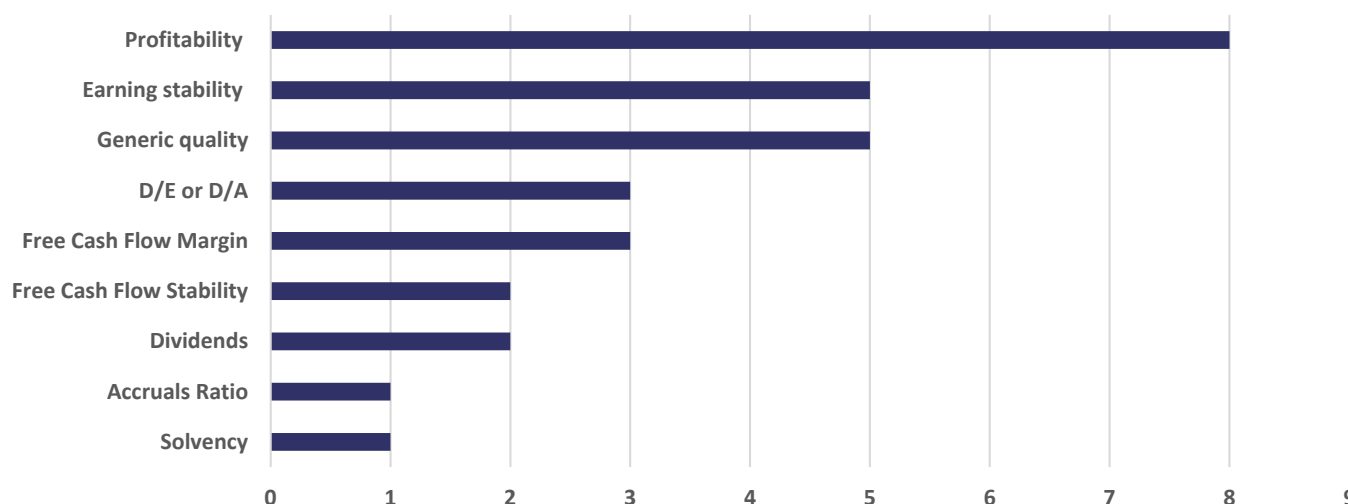


FIGURE 2: Usage of quality sub-factors amongst asset management firms

Source:

Personal research conducted on the construction factors of various quality funds of leading asset management firms.

The figure depicts the frequency in which each quality measure is used to evaluate the stocks in the various analyzed funds.

The firms whose funds were chosen are: Blackrock; AQR; Vanguard; Fidelity; J.P. Morgan, Capital Group, Invesco, Wisdom Tree, Northern Trust, Amundi. One quality fund for each firm was chosen as a sample.

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From Size factor to Illiquidity Factor

In previous fund iterations, the Size factor SMB captured the historical size premium documented by Banz (1981) and Fama and French (1993). However, recent evidence shows that the size effect has weakened or even reversed, particularly during periods of high liquidity and loose financial conditions. Moreover, SMB often conflates firm size with exposure to liquidity and credit constraints, introducing cyclical biases unrelated to genuine risk premia

To address these issues, we replaced the traditional SMB factor with an Illiquidity factor (ILLIQ) following Amihud (2002), which better captures the liquidity risk premium that small-cap stocks were originally thought to proxy.

The ILLIQ factor quantifies the price impact per unit of trading volume, defined as the average ratio of a stock's absolute daily return to its daily dollar volume:

$$ILLIQ_i = \frac{1}{D} \sum_{d=1}^D \frac{|R_{id}|}{VOL_{id}}$$

Where R_{id} is the daily return and VOL_{id} the corresponding dollar volume.

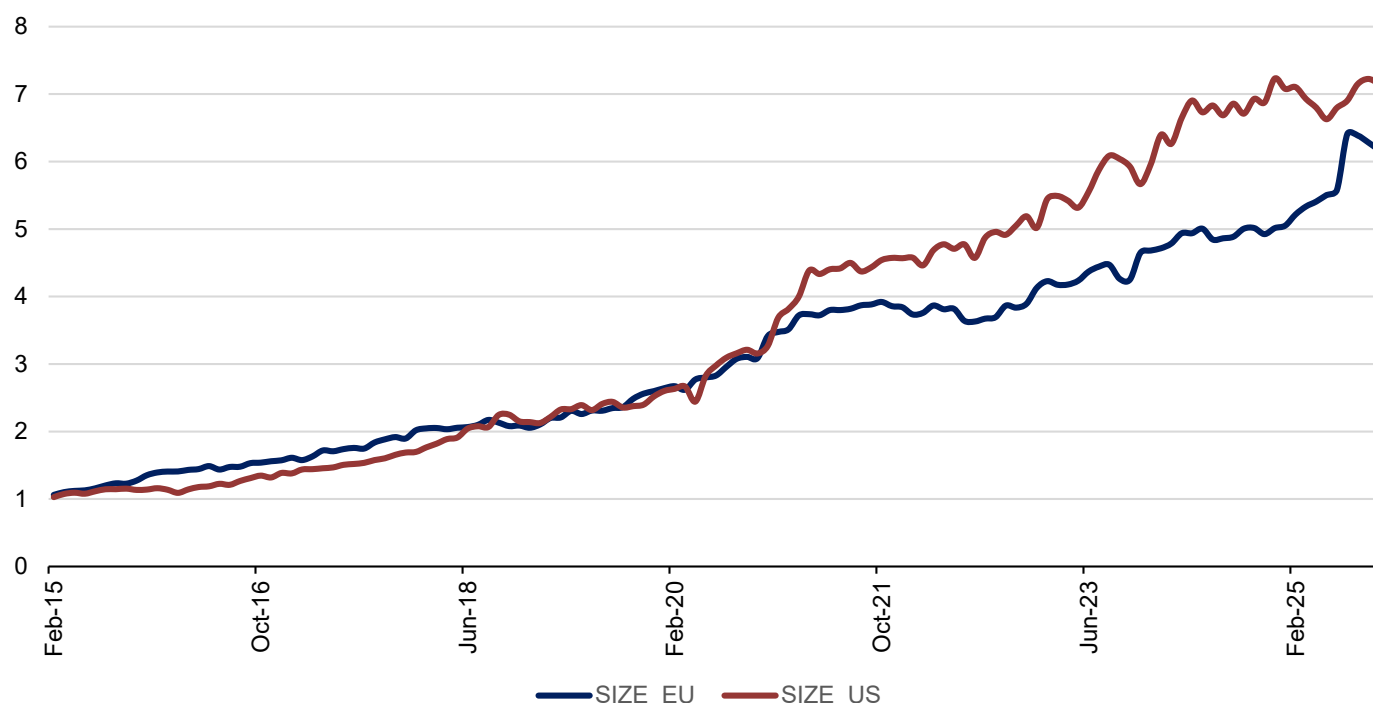
The substitution of the SMB factor with ILLIQ aligns the fund's construction with both academic evidence and practical portfolio considerations. Unlike raw firm size, illiquidity directly measures a priced market friction that influences expected returns and transaction costs, making it a more economically relevant driver of performance.

Moreover, ILLIQ exhibits greater persistence and less sensitivity to cyclical conditions than SMB, whose explanatory power often diminishes in stable, low-volatility markets. Correlation diagnostics indicate that while the Size factor was largely uncorrelated with other components, it added limited diversification benefits; by contrast, ILLIQ introduces exposure to liquidity risk, a distinct and valuable source of systematic return variation.

By focusing on liquidity rather than firm size, the updated specification captures a persistent and economically meaningful source of risk premia that resonates with the current market environment. In today's conditions, characterized by elevated interest rates, tighter financial conditions, and reduced market depth, liquidity risk has re-emerged as a dominant driver of asset pricing. Periods of monetary tightening and declining risk appetite have amplified the dispersion between liquid and illiquid assets, making investors increasingly sensitive to trading costs and market resilience. Consequently, replacing the Size factor with an Illiquidity measure ensures that the portfolio reflects the renewed relevance of liquidity risk as a key determinant of equity performance in the current tightening cycle

The ILLIQ factor strengthens the fund's defensive positioning amid heightened volatility, complementing the stabilizing exposures of Quality and Low Volatility factors within a market still adapting to post-tightening liquidity constraints.

ILLIQ Long-Short: Cumulative Performance



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Value Factor

In earlier versions of the model, the fund relied on the traditional Fama–French High-Minus-Low (HML) factor to capture the value premium. HML sorts stocks by book-to-market (B/M) and takes a long position in “cheap” firms (high B/M) and a short position in “expensive” firms (low B/M). However, over the last decade, the classical value premium has weakened in several markets, especially during long periods of low interest rates, high sector concentration, and the rising importance of intangible-heavy companies. Under these conditions, the standard HML series tends to reflect the structure of the broad CRSP universe rather than the characteristics of the indices in which the fund actually invests.

To address this issue, we construct our Value factor directly from the S&P 500 and STOXX Europe 600. This ensures that the factor reflects only the stocks we can trade and avoids exposures that do not exist in our investment universe. Our factor follows the standard academic B/M definition but aligns it with the fund’s own investment universe, risk framework, and portfolio-construction process. The factor is built monthly using the formula:

$$Book\ Equity_i = BVPS_i \times Shares\ Outstanding_i$$

$$Value\ Signal_i = \frac{B}{M}_i = \frac{Book\ Equity_i}{Market\ Cap_i}$$

To remove the interaction between Value and Size, the cross-section is split by median market capitalization into Small and Big buckets. The median-split procedure ensures the Value factor captures fundamental cheapness and not exposure to small-cap risk. Within each bucket, we identify the top 20% high-B/M stocks (Value) and bottom 20% low-B/M stocks (Growth). These long and short selections are then combined into one size-neutral HML-style portfolio. Signals are lagged by one month and positions are held for twelve months in overlapping cohorts. It reduces noise from reporting delays and makes the factor more realistic to implement. Book-to-Market remains a meaningful indicator of valuation and captures a risk premium linked to economic uncertainty, earnings sensitivity, and valuation mean-reversion. High-B/M firms usually trade at lower expectations and can be more exposed to shifts in macro conditions, interest-rate movements, and inflation trends.

Recent market behavior highlights these differences across regions.

- In the US, the cumulative performance of the factor has been weak, which reflects the strong dominance of mega-cap growth stocks and the prolonged underperformance of cyclical sectors.
- In Europe, where the sector composition is more value-oriented (financials, industrials, energy), the factor displayed meaningfully stronger recovery during 2021–2024.

Our empirical results confirm these macro patterns.

Cumulative Value Factors



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Improving the factor weightings with Hierarchical Risk Parity Approach

Before this adjustment, the fund relied on the Mean-Variance optimization strategy to determine the stock weights in the portfolio, which was introduced last semester. This strategy followed the approach developed by *Harry Markowitz (1952)* in the “*Portfolio selection*” paper and lies at the core of the Modern Portfolio Theory. This semester, we have improved our risk management using the Hierarchical Risk Parity (HRP) approach to select final weights for our stocks in long and short legs.

The Hierarchical Risk Parity (HRP) framework, based on the probabilistic graph theory and machine learning methods, was introduced by López de Prado (2016, *Journal of Portfolio Management*) as an alternative to the traditional Markowitz Mean-Variance Optimization (MVO) (Markowitz, 1952), which we implemented last semester.

The main advantages of the HRP over MVO approaches lie in the model specification. In particular, MVO suffers from numerical instabilities, and the fact that when the variance-covariance matrix is being inverted, the weights may drastically change with slight changes in inputs because this process amplifies the noise from empirical estimates and may produce extreme weights that do not perform well when treated out of sample.

HRP addresses these instabilities, estimation error, and reduces the sensitivity to input assumptions by using modern machine learning estimates and implementing hierarchical clustering to produce portfolios without relying on matrix inversion and expected return forecasts. Finally, López de Prado’s empirical results show that HRP portfolios deliver higher out-of-sample Sharpe ratios and lower turnover than MVO. HRP’s hierarchical clustering also implicitly captures structural dependencies in financial markets, mitigating the effects of multicollinearity and concentration risk.

In order to implement the HRP, we first transformed empirical asset correlations into a distance matrix defined as of the following form:

$$d_{ij} = \sqrt{\frac{1}{2}(1 - \rho_{ij})},$$

Where ρ_{ij} is the Pearson correlation between assets i and j . This transformation ensures that perfectly correlated assets have zero distance, while perfectly anti-correlated assets have maximal distance equal to one. This metric satisfies Euclidean distance properties and allows for hierarchical clustering of assets based on their co-movement patterns. In other words, we cluster assets into groups that tend to move in the same way.

Next, using agglomerative clustering (in our case, we applied single linkage), we have created the hierarchical tree of asset relationships. The assets were next reordered using quasi-diagonalization, which is a way to transform a covariance matrix such that correlated assets are placed adjacently.

Finally, we employed the recursive bisection to divide the tree into progressively smaller clusters, assigning weights inversely proportional to each cluster’s risk contribution. The result is a portfolio where risk is evenly distributed across the hierarchy rather than capital being concentrated in highly correlated assets. This step is similar to other risk parity approaches.

The final portfolio weights ensure that no single cluster dominates total portfolio variance. Moreover, since we are not simply optimizing portfolio weights but running a long-short strategy, we have applied the HRP framework separately to the long and short legs derived from factor portfolios as described in the stock selection step. By applying the HRP to each side and normalizing such that the long and short legs sum to zero, the resulting combined portfolio maintains market neutrality while optimizing risk diversification across both exposures.

We note that despite applying this method, we have set a discretionary cap on every single equity in the portfolio to be at most 5% of the total leg (either long or short) to diversify our exposure. After running empirical tests, the HRP model sometimes gives extreme weights to some stocks due to data availability and historical correlation. These are mostly computational problems, and hence, to mitigate them, we proportionally reassigned the weight from overweighted to underweighted equities to achieve a more balanced allocation.

Additionally, we consider stocks from the US and the EU separately to make our portfolios market-specific. Despite the fact that we neglect the correlation structure between the two geographical areas, we maintain geographic market neutrality. This produces a balanced allocation where both legs contribute equally to overall portfolio volatility, yielding improved risk-adjusted performance.

In the same way, we reckon that this method somehow contradicts the logic of portfolio optimization using all assets in the investible universe. Nevertheless, applying the HRP allows us to study the correlation structure of the stocks selected by our model. And then subsequently, improve the overall fund performance by combining our market outlook with the modern methods of minimizing the variance in the post-selection step.

The MVO approach has produced fruitful results, and therefore, we decided to move in this direction and introduce an empirically superior method to improve our weight selection procedure. Nevertheless, we are exploring a totally automated way to make the selection of the factor weights. Time-series and Bayesian statistical models may be employed, which will not only optimize the portfolio allocation to each stock but also make an improvement to the fund because the weights of the factors themselves will be selected in way that will be most optimal given the current state of the stock market and would allow us to generate a strategy exploiting this edge.

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Mean-Variance Optimization (MVO)

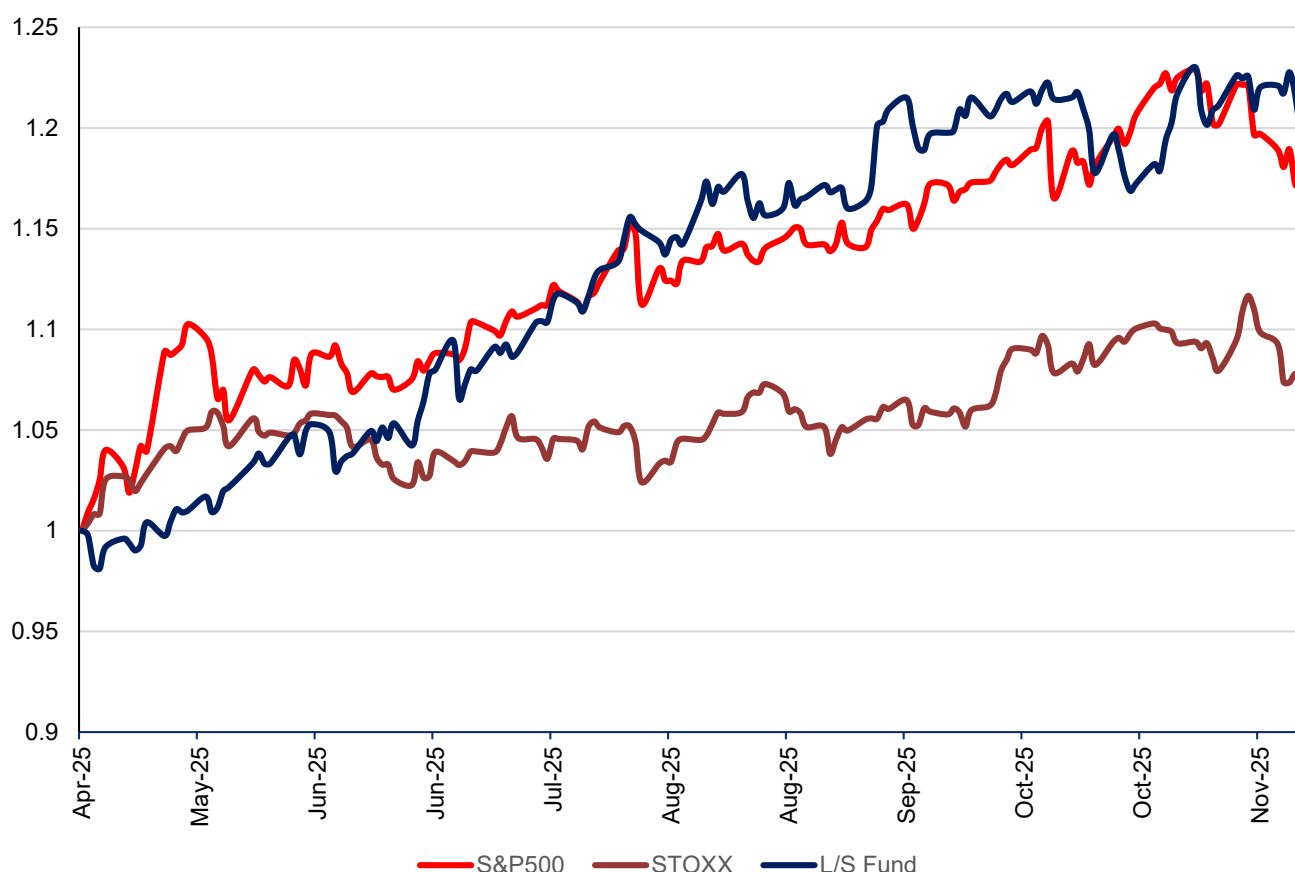
Our portfolio construction relies on Mean–Variance Optimization (MVO), a quantitative framework that identifies the most efficient allocation of capital by balancing expected returns against individual stock risk and cross-asset correlations. The optimization naturally increases exposure to stocks with stronger risk-adjusted profiles, those that combine lower volatility with consistent return patterns while reducing weights in assets that contribute disproportionately to total portfolio risk. This semester, the process proved effective: by concentrating larger weights on less risky and more stable names, the portfolio captured smoother performance streams and generated stronger profits, demonstrating how MVO enhances efficiency and return potential in a long–short structure. In practice, this meant tilting the portfolio toward stocks that improved diversification while limiting exposure to high-volatility positions. As market conditions became more uncertain, the model consistently prioritized resilience over aggressiveness, helping the fund avoid large drawdowns. The result is a more stable performance path that reflects the strength of a risk-aware, systematically optimized allocation.

The chart clearly shows how the Long/Short Fund (blue line) outperforms both the S&P 500 (red) and the STOXX Europe 600 (orange) over the April–November 2025 period. This relative strength reflects the impact of Mean–Variance Optimization (MVO) on our portfolio construction. Through MVO, we systematically allocate larger weights to stocks with stronger risk-adjusted profiles, assets that exhibit lower volatility, more stable return patterns, and beneficial diversification effects.

As a result, the portfolio captures steadier performance streams and avoids concentration in high-risk names that would increase drawdowns. In this semester, the optimization pushed more capital toward less risky but consistently performing stocks, which supported a smoother upward trend in the fund's value. This is visible in the blue line's more stable and persistent growth compared with the more volatile movements of the STOXX, and even the sharper fluctuations of the S&P500.

Overall, the graph illustrates the practical effect of MVO: by favouring lower-risk, high-quality exposures, the fund achieves higher cumulative returns with better risk control, validating the robustness of our long–short allocation framework.

Normalized Performance: L/S fund vs S&P500 and STOXX Europe 600



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Performance

The last portfolio allocation took place on April 28th 2025. Therefore, our timeframe covers the six months and 21 days from April 28th 2025 to November 21st 2025. Over this period, the portfolio generated an **absolute return of €7,856.10** on a total exposure of €100,000, corresponding to a **+7.86% performance** and approximately **+13.6% on an annualized basis**.

Looking at cumulative performance since November 21st 2021, the inception of the fund, **the portfolio has reached a total cumulative performance of €48,294.62**. As in previous years, more than half of this substantial increase was concentrated in the first months of activity.

Keeping in mind that the net invested capital in this fund is zero Euros, **our benchmark is to deliver positive returns**, an objective we achieved both this semester and in the life of the fund.

During this semester, the best performer was the STOXX EUROPE 600 long-short leg, which produced gains for **€ 5482**. To compare, the S&P 500 long-short leg contributed with the lower but still very positive amount of **€ 2374,14**. After a constant increasing from late April to mid October, the portfolio performance slightly dropped in late October. October was particularly challenging with losses in both the STOXX Europe 600 and S&P long-short positions. However, immediately later that month a strong rebound allowed both legs to recover their losses, the portfolio kept stable from October to November 2025, despite that it ended our period with a moderate drop.

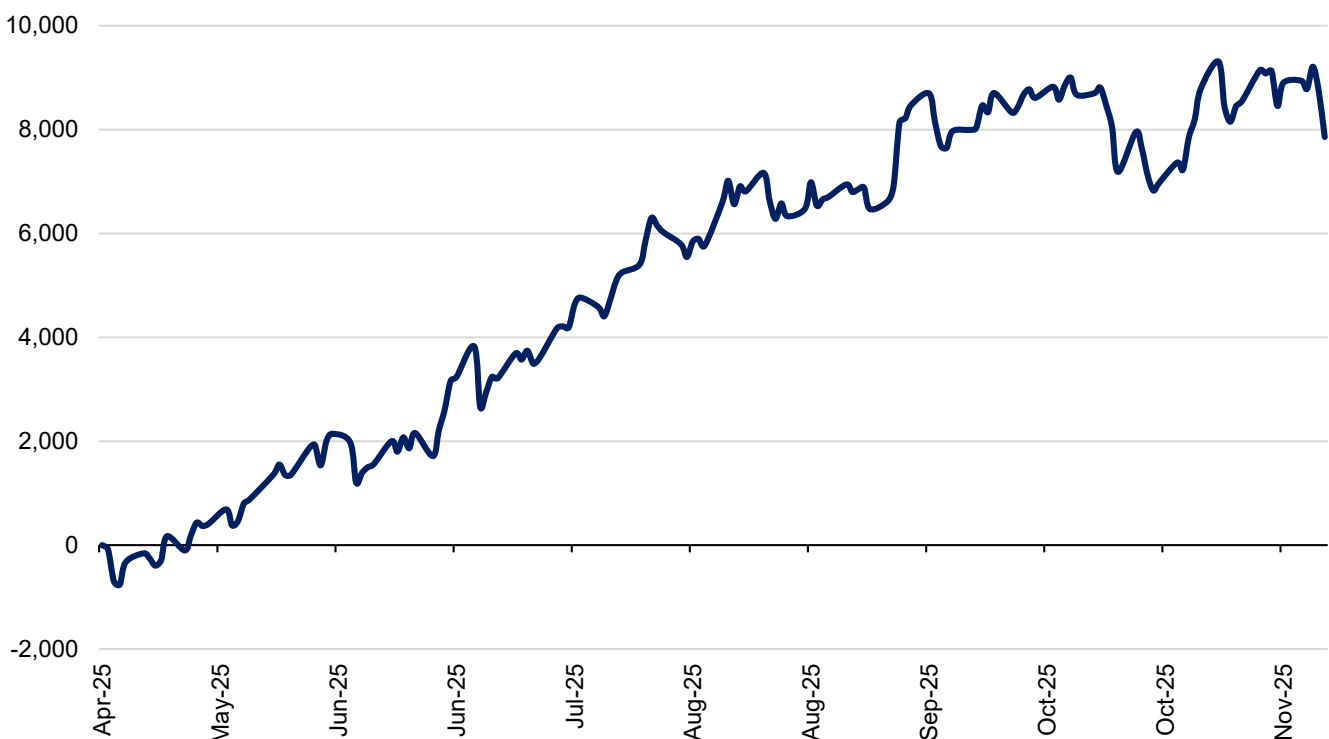
By diving more deeply, we can see that the **best performers** in the S&P 500 leg of the portfolio were **Newmont Corporation**. (long, +53.2% over the period), followed by **Howmet Aerospace Inc** (long, +43.59%) and **Get Carnival Corp** (long, +39.77%). The worst performers were instead **Estée Lauder Companies Inc** (short, +50.82%) **Get Monolithic Power Systems Inc** (short, +30.58%) and **Rockwell Automation, Inc** (short, +19.32%). We can then say that the best performers were represented by long position, while the worst performances by short positions.

Looking at the **STOXX Europe 600 leg**, the **best performances** come from **Siemens Energy AG** (long, +47.71% over the period), **Symrise AG** (short, -27.16%) and **KGHM Polska Miedz** (long, +26.25%). The worst performers were instead **TeamViewer SE** (long, -58.34%), **InPost SA** (long, -35.31%) and **Snam S.p.A.** (short, +6.94%).

In this leg it is possible to observe a slightly different trend with respect to the US one, not only but mainly the long position is representing the best performances and short one the worst performances.

Overall, the fund delivered a positive return despite a volatile market environment. The use of **mean-variance optimization (MVO)** played a key role, as assets with stronger risk-adjusted profiles received higher weights, ultimately supporting the fund's resilience. Since inception, this disciplined factor-based and MVO-driven allocation has consistently produced stable and positive results.

Performance in € (28 April 2025 – 21 November 2025)

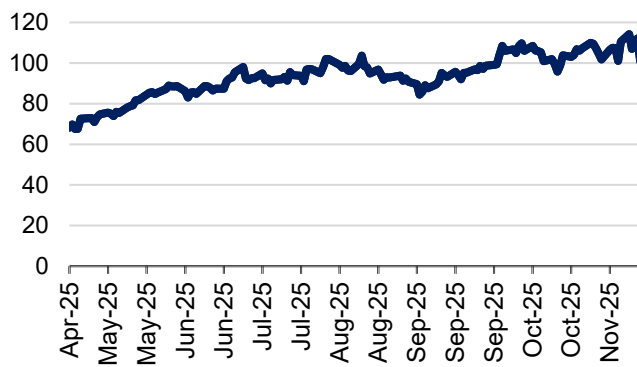


Source: Minerva Investment Management Society and LSEG Workspace. Past performance is not an indicator of future results.

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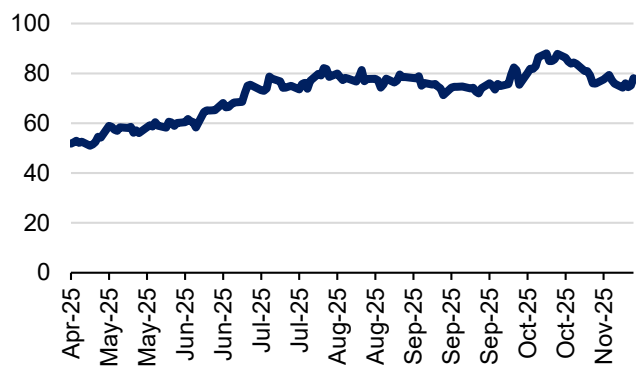
Top Performer: Siemens Energy AG (Long)



Siemens Energy AG is a global leader in energy technology, engaged in the design, engineering, and servicing of power generation and transmission systems. Its business portfolio spans **gas and steam turbines, high-voltage grid infrastructure, hydrogen solutions, and renewable-energy equipment** through its Siemens Gamesa subsidiary. Revenue is distributed across Europe (52%), the Americas (27%), and the Asia-Pacific region (21%). Over the last six months, the company's share price has surged from €68.24 to over €114.25 (17-Nov-2025), marking an exceptional +67% performance, driven by improving operational efficiency, narrowing losses in the wind-turbine division, and robust order inflows for grid modernization and clean-energy projects. Investor confidence was further reinforced by Siemens Energy's progress in stabilizing Siemens Gamesa and securing **major high-voltage transmission contracts aligned with the EU's renewable-infrastructure expansion plan**. Combined with lower financing costs following ECB rate cuts, these developments have positioned Siemens Energy among the best-performing industrial stocks in Europe in 2025.

Source: LSEG Workspace, Total Return Index

Worst Performer: Estée Lauder Companies Inc. (Short)

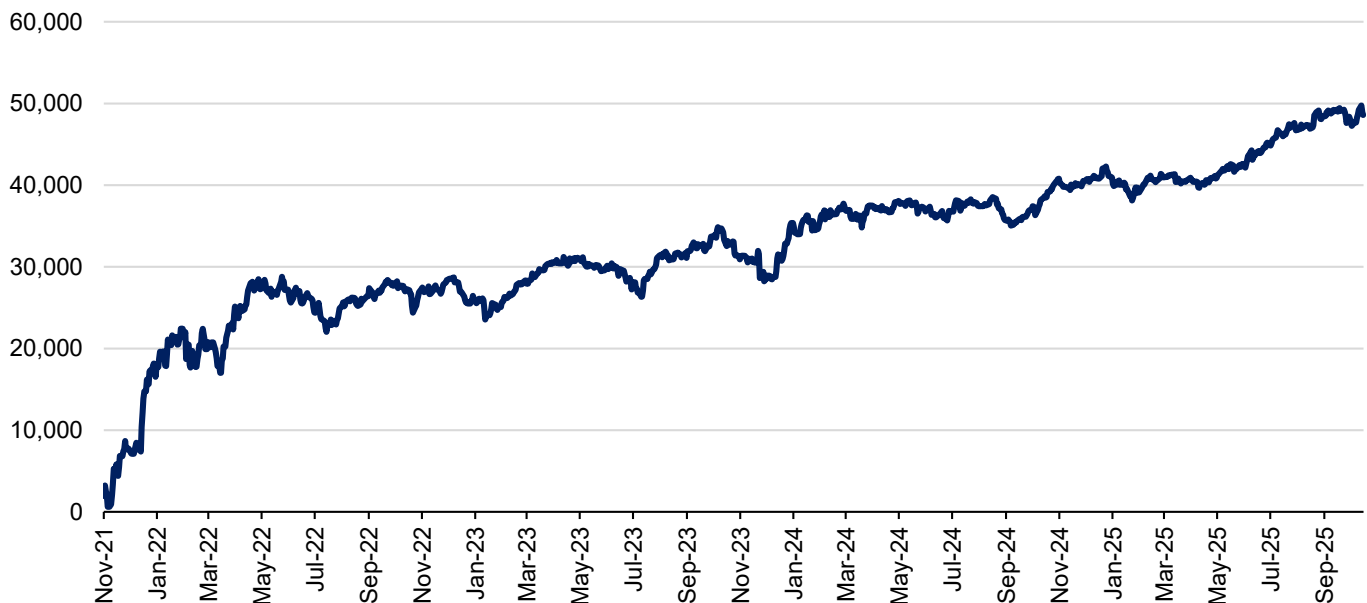


Estée Lauder Companies Inc. is a global leader in prestige beauty, operating across skincare, makeup, fragrance and haircare, with a portfolio of more than 20 premium brands and a strong presence in both travel retail and high-end department stores. The company generates the largest share of its revenue in the Americas and Asia-Pacific, supported by a diversified global distribution network.

Over the past months, Estée Lauder's share price has staged a strong recovery from approximately **€51,1** to **€78,09** driven by improving demand signals in Asia, sequential normalization in the travel-retail channel and a series of restructuring initiatives aimed at restoring profitability. This upward price movement, while positive for the company, resulted in a **negative contribution to our portfolio**, as EL.N was held as a **short position**. Because the stock was **sold at a lower price and subsequently repurchased at a higher price**, the position generated a loss, making EL.N the **worst performer in our long-short strategy for the semester**. The rally was supported by better-than-expected quarterly results, stabilizing inventories across key markets and cost-efficiency measures that improved investor sentiment.

Source: LSEG Workspace, Total Return Index

Cumulative Performance in € (November 21, 2021 – November 21, 2025)



Source: Minerva Investment Management Society and LSEG Workspace. Past performance is not an indicator of future results.

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New Fund Positioning

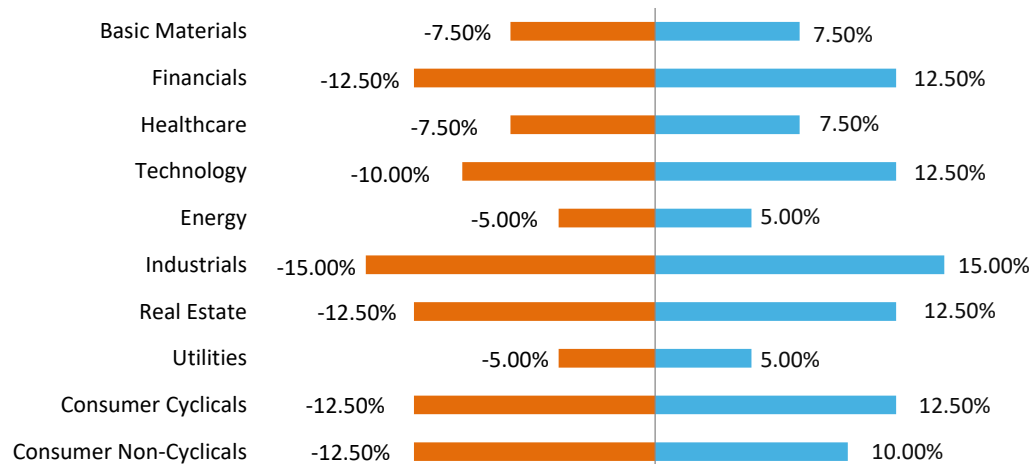
S&P 500

Erie Indemnity Co	5.00%	Expeditors International of Washington Inc	-5.00%
Smurfit WestRock PLC	5.00%	Johnson & Johnson	-5.00%
Regeneron Pharmaceuticals Inc	4.18%	DTE Energy Co	-5.00%
Nextera Energy Inc	3.96%	Loews Corp	-4.46%
Assurant Inc	3.95%	Berkshire Hathaway Inc	-3.79%
Huntington Ingalls Industries Inc	3.44%	Omnicom Group Inc	-3.42%
Arch Capital Group Ltd	3.11%	MGM Resorts International	-3.07%
SBA Communications Corp	2.85%	ConocoPhillips	-2.93%
Extra Space Storage Inc	2.79%	Wells Fargo & Co	-2.74%
Deckers Outdoor Corp	2.33%	Sysco Corp	-2.29%
Estee Lauder Companies Inc	1.78%	Microchip Technology Inc	-2.07%
Super Micro Computer Inc	1.59%	American Express Co	-1.96%
Molina Healthcare Inc	1.46%	Palantir Technologies Inc	-1.73%
Lululemon Athletica Inc	1.44%	Moderna Inc	-1.42%
Old Dominion Freight Line Inc	1.41%	Simon Property Group Inc	-1.12%
Applovin Corp	1.40%	Freeport-McMoRan Inc	-1.09%
Builders FirstSource Inc	1.35%	Host Hotels & Resorts Inc	-0.92%
Texas Pacific Land Corp	1.07%	Occidental Petroleum Corp	-0.74%
Dexcom Inc	1.04%	Marriott International Inc	-0.72%
Epam Systems Inc	0.84%	Wynn Resorts Ltd	-0.53%

STOXX 600

FinecoBank Banca Fineco SpA	5.00%	Syensqo NV	-5.00%
Redeia Corporacion SA	5.00%	Galderma Group AG	-5.00%
Hemnet Group AB (publ)	5.00%	Haleon PLC	-5.00%
RENK Group AG	5.00%	Primary Health Properties PLC	-4.56%
Dino Polska SA	5.00%	Unilever PLC	-3.85%
Neste Oyj	3.82%	Swisscom AG	-3.81%
Hensoldt AG	3.75%	Allreal Holding AG	-3.28%
Prysmian SpA	2.74%	Mobimo Holding AG	-3.04%
Mycronic AB (publ)	2.46%	Daimler Truck Holding AG	-2.86%
Stora Enso Oyj	2.33%	Reckitt Benckiser Group PLC	-2.67%
Valmet Oyj	2.31%	Koninklijke KPN NV	-2.15%
Lifco AB (publ)	1.51%	National Grid PLC	-1.79%
Lagercrantz Group AB	1.42%	Intertek Group PLC	-1.47%
EQT AB	1.23%	HSBC Holdings PLC	-1.35%
SSAB AB	0.96%	Wise PLC	-1.19%
Unibail-Rodamco-Westfield SE	0.96%	Rio Tinto PLC	-0.84%
Sagax AB	0.73%	Barclays PLC	-0.73%
Fastighets AB Balder	0.67%	Informa PLC	-0.57%
Carnival PLC	0.08%	Howden Joinery Group PLC	-0.52%
Evolution AB (publ)	0.03%	Rolls-Royce Holdings PLC	-0.32%

Industries breakdown



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Quantitative Research Team

Risk Report – December 2025

Introduction

Measuring and managing downside risk is central to modern portfolio management, particularly for diversified portfolios containing assets with heterogeneous volatility and heavy-tailed return distributions. Traditional risk metrics based on Gaussian assumptions often fail to capture extreme losses observed in financial markets, motivating the use of alternative models that explicitly account for fat tails, volatility clustering, and dynamic dependence structures.

This report analyses the risk profile of a multi-asset long–short equity portfolio using three complementary approaches: a non-parametric historical method, a parametric Student-t model, and a dynamic GARCH-t specification. Daily portfolio returns are constructed from a cross-section of U.S. and European equities using fixed portfolio weights. The historical approach provides a model-free benchmark for Value-at-Risk and Expected Shortfall, while the parametric Student-t framework captures unconditional heavy-tailed behavior. To account for time-varying volatility and conditional tail risk, per-asset GARCH-t models are estimated and aggregated to the portfolio level using the empirical correlation structure.

In addition, the report compares static and conditional tail risk measures and examines the dynamics of portfolio volatility through a rolling GARCH(1,1) specification. This multi-layered framework allows for a comprehensive assessment of portfolio risk under both unconditional and conditional distributions, highlighting the importance of volatility dynamics and tail behavior in risk measurement.

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where $\mathbf{R}$ denotes the return matrix and $\mathbf{w}$ the weight vector. In the implementation, portfolio returns are computed via a matrix multiplication between the return matrix and the weight vector.

A final consistency check ensures that the ordering of asset returns exactly matches the ordering of portfolio weights before the computation is performed. The resulting portfolio return series is then stored as a time-indexed vector, preserving the original trading dates. This series represents the daily performance of the long–short strategy and constitutes the basis for all subsequent performance and risk analysis.

Per-Asset Risk Modelling

To assess the risk profile of the individual assets in the portfolio, daily returns are modelled on a per-asset basis using a Student-t distribution. For each asset i , we assume

$$R_{t,i} \sim t_{\nu_i}(\mu_i, \sigma_i^2)$$

where μ_i denotes the location parameter (mean), σ_i the scale parameter (volatility) and ν_i the degrees of freedom controlling tail thickness. The parameters μ_i and σ_i are estimated by the sample mean and sample standard deviation of the historical return series.

The degrees of freedom ν_i are selected via a Kolmogorov–Smirnov (KS) goodness-of-fit procedure. Specifically, for each candidate $\nu \in \{2, \dots, 99\}$, synthetic returns are simulated from a Student-t distribution with parameters (μ_i, σ_i, ν) and the two-sample KS statistic is computed between the simulated sample and the empirical returns of asset i . The value ν_i is chosen as the minimiser of this KS distance, thereby selecting the Student-t specification whose distribution is closest to the empirical one in the KS sense.

Portfolio Return Computation

Once the matrix of daily asset returns has been constructed and aligned with the portfolio allocation vector, portfolio returns are computed through a matrix–vector product. Let $R_{\{t,i\}}$ denote the daily return of asset i at time t and let w_i be its corresponding portfolio weight. The portfolio return at time t is defined as

$$R_t^p = \sum_{i=1}^N w_i R_{t,i}$$

In vector notation, this can be written compactly as

$$\mathbf{R}^p = \mathbf{R}\mathbf{w},$$

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Per-Asset Risk Modelling (continued)

Given the fitted Student-t model, one-day parametric Value-at-Risk (VaR) and Expected Shortfall (ES) are computed at the 95% and 99% confidence levels. For a one-day horizon and tail probability α (e.g. $\alpha = 0.05$ or $\alpha = 0.01$), the per-asset VaR is given by

$$\text{VaR}_{\alpha,i} = \mu_i + \sigma_i t_{v_i}^{-1}(\alpha),$$

where $t_{v_i}^{-1}(\alpha)$ denotes the α -quantile of the standard Student-t distribution with v_i degrees of freedom. The corresponding ES has a closed-form expression under the Student-t assumption:

$$\text{ES}_{\alpha,i} = \mu_i - \sigma_i \frac{v_i + q_{\alpha,i}^2}{v_i - 1} \frac{f_{v_i}(q_{\alpha,i})}{\alpha},$$

where $q_{\alpha,i} = t_{v_i}^{-1}(\alpha)$ and f_{v_i} denotes the Student-t probability density function with v_i degrees of freedom. These measures provide a static, distribution-based assessment of the tail risk of each individual asset over a one-day horizon, taking into account fat tails through the estimated degrees of freedom. Tables 1 and 2 report the five riskiest and five safest assets in the portfolio according to the Expected Shortfall at the 95% confidence level. Expected Shortfall measures the expected loss conditional on extreme negative outcomes and therefore provides a coherent metric of tail risk.

The worst-performing assets in terms of downside risk include SMCI, MRNA, and MOH, all of which exhibit high volatility and relatively heavy tails, as reflected by their large Expected Shortfall values. In particular, SMCI shows an $\text{ES}_{0.95}$ close to -9.4%, indicating substantial expected losses during extreme market downturns. These assets contribute disproportionately to tail risk and are therefore critical drivers of portfolio risk under stressed conditions. Conversely, the safest assets, such as DTE, URW.PA and ALLN.SW, display significantly lower volatility and much smaller tail losses, with $\text{ES}_{0.95}$ values close to -1.5%. These stocks provide natural risk stabilization within the portfolio and behave more defensively during adverse market movements.

Overall, this ranking highlights the strong heterogeneity in tail risk across assets and confirms the importance of modeling heavy tails when evaluating risk in long-short equity portfolios.

Conditional Risk Modelling with GARCH-t

The static Student-t specification provides a distributional description of unconditional returns, but it does not account for time-variation in volatility.

To incorporate volatility clustering, we estimate, for each asset i , a univariate GARCH model with Student-t innovations of the form

$$R_{t,i} = \mu_i + \varepsilon_{t,i}, \quad \varepsilon_{t,i} = \sigma_{t,i} z_{t,i},$$

where the conditional variance follows

$$\sigma_{t,i}^2 = \omega_i + \sum_{j=1}^{p_i} \alpha_{i,j} \varepsilon_{t-j,i}^2 + \sum_{k=1}^{q_i} \beta_{i,k} \sigma_{t-k,i}^2$$

and the standardized innovations $z_{t,i}$ are assumed to follow a Student-t distribution with $v_i^{(\text{GARCH})}$ degrees of freedom. For each asset, the orders (p_i, q_i) are selected by minimising the Bayesian Information Criterion over a grid of candidate specifications.

From the fitted GARCH-t model, we obtain the one-step-ahead conditional mean and variance forecasts, denoted by $\mu_{i,t+1}^{(\text{G})}$ and $\sigma_{i,t+1}^{(\text{G})}$, as well as the estimated degrees of freedom $v_i^{(\text{GARCH})}$. Under this conditional distributional assumption, the one-day ahead Value-at-Risk and Expected Shortfall at tail probability α are given by

$$\text{VaR}_{\alpha,i}^{(\text{GARCH})} = \mu_{i,t+1}^{(\text{G})} + \sigma_{i,t+1}^{(\text{G})} t_{v_i^{(\text{GARCH})}}^{-1}(\alpha),$$

$$\text{ES}_{\alpha,i}^{(\text{GARCH})} = \mu_{i,t+1}^{(\text{G})} - \sigma_{i,t+1}^{(\text{G})} \frac{v_i^{(\text{GARCH})} + q_{\alpha,i}^2}{v_i^{(\text{GARCH})} - 1} \frac{f_{v_i^{(\text{GARCH})}}(q_{\alpha,i})}{\alpha}$$

where $q_{\alpha,i} = t_{v_i^{(\text{GARCH})}}^{-1}(\alpha)$ and $f_{v_i^{(\text{GARCH})}}$ is the Student-t density. These quantities represent conditional tail risk measures, as they are computed given the current estimated volatility level.

Table 1: Worst 5 Stocks by ES at 95% CI

Ticker	VaR _{0.95}	ES _{0.95}
SMCI	-7.43%	-9.39%
MRNA	-6.39%	-8.22%
MOH	-6.52%	-8.19%
APP	-5.83%	-7.50%
R3NK.DE	-5.85%	-7.40%

Table 2: Best 5 Stocks by ES at 95% CI

Ticker	VaR _{0.95}	ES _{0.95}
DTE	-1.52%	-1.92%
URW.PA	-1.42%	-1.86%
SCMN.SW	-1.41%	-1.80%
MOBN.SW	-1.15%	-1.51%
ALLN.SW	-1.01%	-1.40%

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Conditional Risk Modelling with GARCH-t

Tables 3 and 4 report the five most and least risky assets in terms of 1-day Expected Shortfall at the 99% confidence level under the GARCH-t specification. The riskiest names (DXCM, MOH, EPAM, SMCI, and PLTR) exhibit both elevated conditional volatility and very low estimated degrees of freedom, indicating extremely heavy tails. In particular, DXCM displays an $ES_{0.99}^{(GARCH)}$ of approximately -74%, reflecting the presence of extreme conditional downside risk in periods of high volatility.

In contrast, the safest assets (SY, DTE, URW.PA, MOBN.SW and ALLN.SW) are characterised by low conditional volatility and very large degrees of freedom, with $\nu^{(GARCH)}$ often exceeding 70. This implies that, conditionally, their return distributions are close to Gaussian with relatively thin tails, and their $ES_{0.99}^{(GARCH)}$ values remain below -3% in magnitude. The comparison between static and GARCH-based ES rankings highlights that incorporating time-varying volatility and heavy-tailed innovations can substantially amplify the estimated tail risk for certain growth and technology stocks, while leaving stable, defensive stocks relatively unaffected.

Portfolio Parametric and GARCH-t VaR and ES and Portfolio level risk summary

Having obtained the time series of daily portfolio returns, we next model the distribution of the portfolio as a whole and compute corresponding one-day risk measures. Let R_t^p denote the portfolio return at time t , obtained as a weighted sum of individual asset returns,

$$R_t^p = \sum_{i=1}^N w_i R_{t,i}.$$

From the empirical series $\{R_t^p\}_{t=1}^T$, we estimate the sample mean μ_p and standard deviation σ_p and assume that portfolio returns follow a Student-t distribution

$$R_t^p \sim t_{\nu_p}(\mu_p, \sigma_p^2),$$

with unknown degrees of freedom ν_p .

In order to select ν_p , a Kolmogorov-Smirnov goodness-of-fit procedure analogous to the per-asset case is applied. For each candidate $\nu \in \{2, \dots, 99\}$, synthetic returns are generated from a Student-t distribution with parameters (μ_p, σ_p, ν) and the two-sample KS statistic between the simulated and empirical portfolio returns is computed. The value ν_p is chosen as the minimiser of this distance. In the empirical application, the procedure selects $\nu_p = 54$, indicating relatively thin tails at the portfolio level, consistent with diversification across assets.

Given the fitted Student-t model, one-day portfolio Value-at-Risk (VaR) and Expected Shortfall (ES) at tail probability α are computed as

$$VaR_\alpha^p = \mu_p + \sigma_p t_{\nu_p}^{-1}(\alpha),$$

and

$$ES_\alpha^p = \mu_p - \sigma_p \frac{\nu_p + q_\alpha^2}{\nu_p - 1} \frac{f_{\nu_p}(q_\alpha)}{q_\alpha}$$

where $q_\alpha = t_{\nu_p}^{-1}(\alpha)$ denotes the α -quantile of the standard Student-t distribution with ν_p degrees of freedom and f_{ν_p} is its probability density function.

These quantities provide a parametric estimate of the portfolio's potential one-day loss under extreme market conditions, with ES capturing the average loss beyond the VaR threshold.

To obtain a conditional, model-based measure of portfolio tail risk, we combine the per-asset GARCH-t estimates with the empirical correlation structure between assets. Let $\mu_i^{(G)}$ and $\sigma_i^{(G)}$ denote the one-step-ahead conditional mean and standard deviation forecasts for asset i from its GARCH-t model and let ρ be the $N \times N$ correlation matrix of asset returns. The conditional covariance matrix implied by the GARCH forecasts is then constructed as

$$\Sigma^{(G)} = D \rho D,$$

where $D = \text{diag}(\sigma_1^{(G)}, \sigma_2^{(G)}, \dots, \sigma_N^{(G)})$ is the diagonal matrix of conditional standard deviations.

Given the portfolio weight vector $\mathbf{w}$, the one-step-ahead conditional mean and variance of the portfolio return are

$$\mu_p^{(G)} = \mathbf{w}^\top \boldsymbol{\mu}^{(G)}, \quad \sigma_p^{(G)2} = \mathbf{w}^\top \Sigma^{(G)} \mathbf{w}$$

with $\sigma_p^{(G)} = \sqrt{\mathbf{w}^\top \Sigma^{(G)} \mathbf{w}}$.

Table 3: Top 5 most risky stocks by 1-day ES at 99% (GARCH-t)

Ticker	$ES_{0.99}(\text{GARCH-t})$
DXCM	-73.77%
MOH	-31.23%
EPAM	-30.48%
SMCI	-26.01%
PLTR	-22.28%

Table 3: Top 5 least risky stocks by 1-day ES at 99% (GARCH-t)

Ticker	$ES_{0.99}(\text{GARCH-t})$
SY	-2.93%
DTE	-2.34%
URW.PA	-2.16%
MOBN.SW	-1.63%
ALLN.SW	-1.51%

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The portfolio degrees of freedom $\nu_p^{(G)}$ are approximated by a weight-averaged combination of the per-asset degrees of freedom, which provides an effective tail-thickness parameter for the portfolio.

Assuming that the one-day ahead portfolio return follows a Student-t distribution

$$R_{t+1}^p \sim t_{\nu_p^{(G)}} \left(\mu_p^{(G)}, \left(\sigma_p^{(G)} \right)^2 \right),$$

the corresponding VaR and ES at tail probability α are given by

$$VaR_\alpha^{(GARCH-t)} = \mu_p^{(G)} + \sigma_p^{(G)} t_{\nu_p^{(G)}}^{-1}(\alpha),$$

$$ES_\alpha^{(GARCH-t)} = \mu_p^{(G)} - \sigma_p^{(G)} \frac{\nu_p^{(G)} + q_\alpha^2}{\nu_p^{(G)} - 1} \frac{f_{\nu_p^{(G)}}(q_\alpha)}{\alpha}$$

where $q_\alpha = t_{\nu_p^{(G)}}^{-1}(\alpha)$ and $f_{\nu_p^{(G)}}$ denotes the Student-t density.

This yields conditional, correlation-aware tail risk measures for the portfolio.

Result at Portfolio Level

Table 5 compares the portfolio 1-day VaR and ES obtained from the historical, parametric Student-t, and GARCH-t approaches. All three methods deliver broadly similar risk estimates at the 95% and 99% confidence levels, which suggests that the Student-t specification provides a reasonable parametric approximation to the empirical distribution of portfolio returns.

However, the GARCH-t model systematically produces slightly more conservative (more negative) Expected Shortfall values, particularly at the 99% level.

This reflects the fact that the GARCH specification explicitly accounts for time-varying volatility and conditional clustering of large returns, leading to higher estimated tail losses in periods of elevated risk.

Table 5: Portfolio 1-day VaR and ES under different modelling approaches

Method	VaR _{0.95}	ES _{0.95}	VaR _{0.99}	ES _{0.99}
Historical	-0.94%	-1.18%	-1.38%	-1.49%
Param t	-0.96%	-1.20%	-1.35%	-1.55%
GARCH t	-0.96%	-1.23%	-1.40%	-1.65%

Time-Varying Portfolio Volatility

In order to analyse the dynamics of portfolio risk over time, we construct two measures of time-varying volatility for the portfolio return series. Let R_t^p denote the daily portfolio return. First, a simple rolling volatility measure is computed as the sample standard deviation over a moving window of $w = 60$ trading days,

$$\sigma_t^{(\text{roll})} = \sqrt{\frac{1}{w-1} \sum_{j=1}^w (R_{t-j+1}^p - \bar{R}_t^p)^2},$$

where $\bar{R}_t^p$ is the average portfolio return over the window $\{t-w+1, \dots, t\}$.

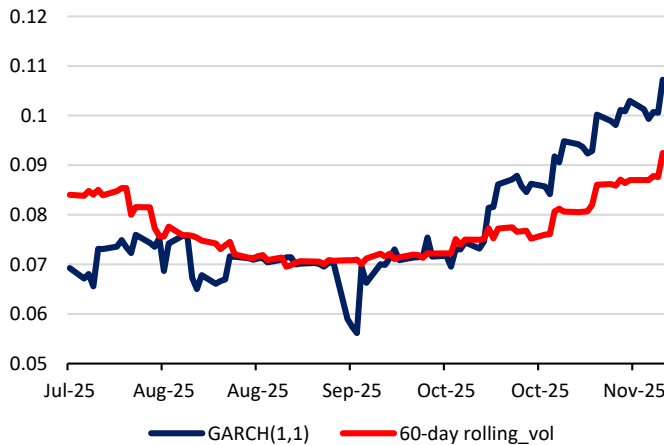
Second, a model-based conditional volatility estimate is obtained from a rolling GARCH(1,1) specification with Student-t innovations. For each time t , the model

$$R_t^p = \mu_t + \varepsilon_{s,t}, \quad \varepsilon_{s,t} = \sigma_{s,t} z_{s,t}, \quad z_{s,t} \sim t_{\nu_t},$$

is re-estimated on the most recent 60 observations $\{R_{t-w+1}^p, \dots, R_t^p\}$, and the one-step-ahead conditional standard deviation $\sigma_{t+1|t}^{(GARCH)}$ is extracted as the GARCH-based volatility estimate at time t . Both volatility series are annualised by multiplying daily standard deviations by $\sqrt{252}$.

Figure 1 compares the annualised GARCH(1,1) volatility to the simple rolling volatility over the sample period. The two measures co-move closely in tranquil periods, while the GARCH-based volatility responds more sharply to clusters of large returns, capturing volatility persistence more effectively than the purely backward-looking rolling standard deviation.

Figure 1: GARCH vs Simple Rolling (annualized)



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