

MIMS – Long-Short Equity Fund

Portfolio Management Team

Report – May 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 with the new term of administration a radical shift in policies was experienced. President Trump's "Liberation Day" tariffs introduced a 10% baseline tariff, with additional reciprocal tariffs under negotiation. This led to significant market volatility and decrease investors' confidence. S&P 500 reacted with a significant drop of 6.65% on April 3rd. Following a market reaction a pause in tariffs was announced with potential negotiations followed to decrease tariffs pressures. The Fed revised GDP growth forecast for the US economy for 2025 down to 1.7%, from an earlier estimate of 2.1%, indicating more modest economic activities. The 0.4% monthly rise in the core PCE measure in February 2025 was the highest since March 2024. It showed that the progress toward the 2% target is likely to be gradual, even though the indicator totalled to 0% in March.
- The Federal Reserve interest rate remained at the level of 4.25%-4.50% since December 2024, with only marginal forecasts for decrease to 3.75%-4% to the end of the year. In the EU interest rates dropped from 3% at the beginning of the year to 2.25% with 3 cuts from ECB. Despite escalated inflation levels, these cuts a part of a broader strategy to ease monetary conditions in the region and boost economic growth in the Union. As a result, in the first quarter of the year, the Eurozone economy grew by 0.4%, doubling the growth of the previous quarter.
- In China, the GDP growth surpassed expectations with a 5.4% YoY growth in the first quarter. The government plans to issue 5.7 trillion yuan to support the economy after record 125% tariffs on most import from China was implemented by the US.
- Markets face significant volatility as investors weigh the impact of political uncertainty. The current outlook for the coming years has driven up long-term US bond yields and started the reverse of the Dollar against the Euro.



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Factor Investing Strategy

VALUE	MOMENTUM
QUALITY	LOW VOLATILITY
SIZE	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 (SMB, Fama & French (1992)), 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 (Beta 1, 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. For instance, to capture the "size" factor, assets can be ranked according to their market capitalization. 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

- The value factor is based on the High-Minus-Low (HML) factor of Fama & French (1992, 1993). The factor exposure is then calculated as the beta to this portfolio in a regression.

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.
- A long-short portfolio is constructed from the above each month of our observation period, and companies' exposure to the portfolio is assessed.

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

- BETA1 of Nelson-Siegel Model : represent the component illustrating the slope changes of the curve. A time-series of betas is used to extract the sensitivity of stocks to the changes in the slope of the curve.

Size Factor – Short position

- SMB factor based on Free-Float Market Capitalization (Fama & French, 1992, 1993). A lower market cap is assumed to be a buy signal, since small-cap stocks have historically shown relatively better performances than large-cap stocks (see Banz (1981). See Reinganum (1981) for empirical evidence in the academic literature). The exposure is taken by reversing the SMB factor in Kenneth French's data library.

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Tactical Decisions

The current climate of uncertainty in capital markets appears to be highly concentrated, with investors; sentiment and overall market direction heavily influenced by the actions and guidance of a single key policymaker. In this light, factor exposures have been adjusted with a conservative bias.

The SMB (Small Minus Big) factor remains in negative territory at -10%. while HML (High Minus Low) has been reduced to 15%. The recent decline in economic indicators, coupled with rising inflation expectations, has increased the likelihood of a stagflationary environment. Such conditions are particularly adverse for smaller firms, which typically possess weaker balance sheets and are more sensitive to tightening financial conditions. Persistently high interest rates and limited pricing power may force these companies to refinance debt at unfavorable terms, while also facing pressure on revenues due to their relatively undifferentiated product offerings and greater exposure to substitution risk.

The Quality (QLT) factor has been maintained at 25%. reflecting our conviction that strong fundamentals are a key driver of equity performance amid heightened volatility. Core components of this factor include return on equity (ROE), ROE growth, debt-to-equity ratio, safety (measured as total liabilities relative to operating cash flow), and EVOL (volatility of ROE).

Momentum (MOM) has been reduced to 10%. while Low Volatility (LVOL) has been lowered to 25%. Recent episodic spikes in market volatility may have temporarily distorted these factors by introducing short-term reversals or amplifying transient trends. As such, current signals may reflect non-structural movements in equity returns that are unlikely to persist over time.

Finally, we have introduced a new factor, BETA1, assigning to it a weight of 15%. This factor captures the sensitivity of individual equity returns to changes in the steepness of the yield curve.,as estimated using the Nelson-Siegel model. The recent curve steepening, alongside elevated inflation expectations and declining confidence in U.S. Treasuries. supports a long position in BETA1 at this point of the current U.S. administration term.

Factor weights

Value (15%)	High-Minus-Low Book-to-Market (HML) Factor	15%
Inverted Size (10%)	Small-Minus-Big Market Capitalization	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	5.5%
Low Volatility (25%)	Standard deviation of idiosyncratic errors from factor model	25%
BETA1 (15%)	Beta 1 coefficient of the Nelson-Siegel yield curve estimation method	15%

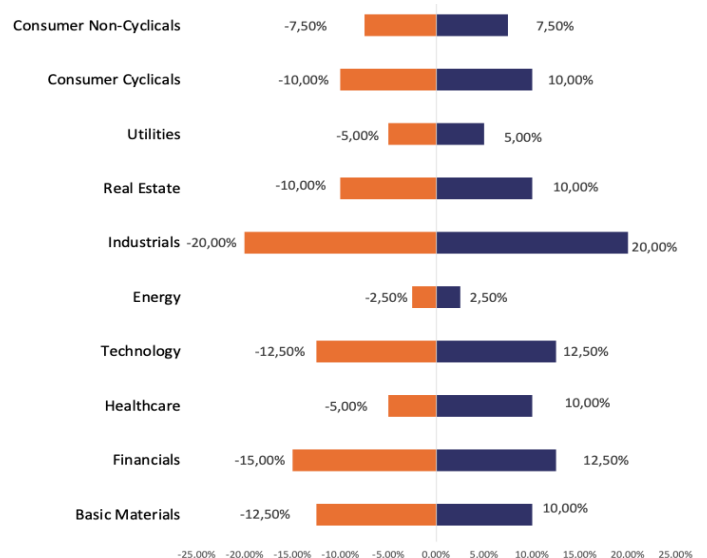
New Fund Positioning

S&P 500					
Howmet Aerospace Inc	4,99%	0,72	Invitation Homes Inc	4,99%	-1,02
Ventas Inc	4,99%	0,71	Costco Wholesale Corp	4,99%	-0,88
Royal Caribbean Cruises Ltd	4,99%	0,82	Dover Corp	3,94%	-0,96
Uber Technologies Inc	2,61%	1,01	Estee Lauder Companies Inc	3,81%	-0,67
Super Micro Computer Inc	2,20%	1,17	3M Co	2,12%	-0,93
Simon Property Group Inc	2,06%	0,60	BlackRock Inc	2,03%	-0,93
Newmont Corporation	2,06%	0,54	Marsh & McLennan Companies Inc	2,02%	-1,18
Insulet Corp	2,03%	0,62	Paychex Inc	2,02%	-0,79
Kenvue Inc	2,01%	1,84	ANSYS Inc	2,02%	-0,74
Lamb Weston Holdings Inc	2,01%	0,60	Paycom Software Inc	2,01%	-0,74
United Airlines Holdings Inc	2,01%	0,89	Equinix Inc	2,01%	-0,83
PG&E Corp	2,01%	1,06	Keysight Technologies Inc	2,01%	-0,69
Verato Corp	2,01%	0,88	Prologis Inc	2,01%	-0,78
CF Industries Holdings Inc	2,01%	0,65	Illinois Tool Works Inc	2,01%	-1,28
Carnival Corp	2,01%	0,64	Home Depot Inc	2,01%	-0,81
Freeport-McMoRan Inc	2,00%	0,52	Monolithic Power Systems Inc	2,01%	-0,85
Delta Air Lines Inc	2,00%	0,70	Pool Corp	2,00%	-0,79
Norwegian Cruise Line Holdings Ltd	2,00%	0,54	Rockwell Automation Inc	2,00%	-1,17
Akamai Technologies Inc	2,00%	0,52	T Rowe Price Group Inc	2,00%	-0,99
Moderna Inc	2,00%	0,49	Aptiv PLC	2,00%	-0,82
STOXX EUROPE 600					
Rolls-Royce Holdings PLC	5,00%	1,22	Croda International PLC	4,97%	-0,74
Siemens Energy AG	5,00%	1,17	Ems Chemie Holding AG	4,90%	-0,75
Banco de Sabadell SA	4,99%	1,19	Symrise AG	4,86%	-0,61
Banco BPM SpA	2,80%	1,40	Snam SpA	2,85%	-0,60
PKO Bank	2,14%	1,15	Lonza Group AG	2,29%	-0,52
BPER Banca SpA	2,04%	1,41	Tomra Systems ASA	2,05%	-0,89
Klepierre SA	2,01%	1,04	Wolters Kluwer NV	2,03%	-0,65
Accelleron Industries AG	2,01%	1,33	Givaudan SA	2,02%	-0,61
Sandoz Group AG	2,00%	1,14	Allreal Holding AG	2,01%	-0,61
Haleon PLC	2,00%	1,50	Ashtead Group PLC	2,01%	-0,65
DSM-Firmenich AG	2,00%	2,32	Halma PLC	2,00%	-0,82
Unibail-Rodamco-Westfield SE	2,00%	1,16	Roche Holding AG	2,00%	-0,58
AIB Group PLC	2,00%	1,11	Viscofan SA	2,00%	-0,61
Centrica PLC	2,00%	1,37	Nibe Industrier AB	2,00%	-0,77
InPost SA	2,00%	1,25	Groep Brussel Lambert NV	2,00%	-0,78
LPP SA	2,00%	1,17	St James's Place PLC	2,00%	-0,75
Telecom Italia SpA	2,00%	1,12	Pennon Group PLC	2,00%	-0,44
KGHM Polska Miedz SA	2,00%	1,06	Spirax Group PLC	2,00%	-0,85
TeamViewer SE	2,00%	1,07	Kinnevik AB	2,00%	-0,68
Azelis Group NV	2,00%	1,28	Oersted A/S	2,00%	-0,61

Weight & Score Long

Weight & Score Short

Industries breakdown



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Neutrality Hedges

Given the companies in our proposed portfolio allocation, we achieved a reduction in betas in absolute values for STOXX EURO 600 index and a small increase in the beta for S&P 500 when compared to the previous portfolio allocation.

For the European leg of the portfolio, the 10 year historical beta using monthly observations has been 0.0725. For the US leg, the raw monthly beta has been 0.1004. We observe that there is no significant difference between the US beta and the EU beta as we witnessed last semester.

In this semester we decided not to introduce the hedging against the market movements due to small values of betas, despite their statistical significance with a level of 95%. We can see from the plots below there is no clear linear relationship between our portfolios and the S&P 500 and STOXX EURO 600. As a result, we do not need any beta hedging to stay neutral to the underlying movements in the indices.

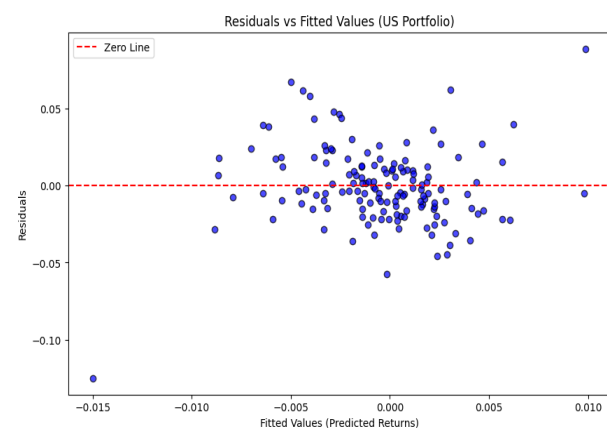
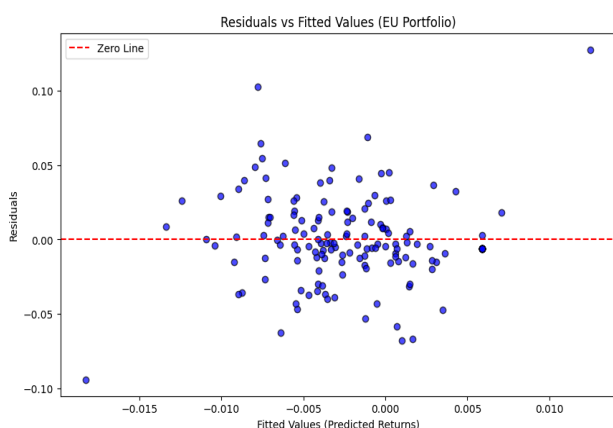
It is important to note that beta exposures are subject to change over time, which could result in significant variations in the portfolio's beta within weeks or months. Maintaining a consistently beta-neutral position would require dynamic hedging with futures on the underlying indices. However, this approach is not employed in this fund, since portfolio allocations are rebalanced only on a semiannual basis.

Another risk faced by the fund is currency risk. At inception, the fund's currency risk is zero, as it is structured as a zero-initial-investment fund. However, similar to beta exposure, currency risk may evolve over time, as the payout in USD may not perfectly correlate with the payout in EUR. Currently, no currency hedging measures have been implemented.

OLS Regression Analysis of EU and US Portfolio Returns

OLS Regression Results					
Dep. Variable:	EU Portfolio Returns	R-squared:	0.027		
Model:	OLS	Adj. R-squared:	0.020		
Method:	Least Squares	F-statistic:	4.189		
Date:	Thu, 08 May 2025	Prob (F-statistic):	0.0424		
Time:	07:30:51	Log-Likelihood:	346.12		
No. Observations:	154	AIC:	-688.2		
Df Residuals:	152	BIC:	-682.2		
Df Model:	1				
Covariance Type: nonrobust					
	coef	std err	t	P> t	[0.025 0.975]
const	-0.0030	0.002	-1.370	0.173	-0.007 0.001
STOXX Europe 600	0.0725	0.035	2.047	0.042	0.003 0.142
Omnibus:	17.302	Durbin-Watson:	1.513		
Prob(Omnibus):	0.000	Jarque-Bera (JB):	36.358		
Skew:	0.470	Prob(JB):	1.27e-08		
Kurtosis:	5.187	Cond. No.	17.1		

OLS Regression Results					
Dep. Variable:	US Portfolio Returns			R-squared:	0.038
Model:	OLS			Adj. R-squared:	0.031
Method:	Least Squares			F-statistic:	5.629
Date:	Thu, 08 May 2025			Prob (F-statistic):	0.0190
Time:	07:30:51			Log-Likelihood:	344.48
No. Observations:	146			AIC:	-685.0
Df Residuals:	144			BIC:	-679.0
Df Model:	1				
Covariance Type: nonrobust					
	coef	std err	t	P> t	[0.025 0.975]
const	-0.0011	0.002	-0.572	0.568	-0.005 0.003
S&P 500	0.1004	0.042	2.373	0.019	0.017 0.184
Omnibus:	20.098	Durbin-Watson:		2.060	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		54.042	
Skew:	0.479	Prob(JB):		1.84e-12	
Kurtosis:	5.822	Cond. No.		22.2	



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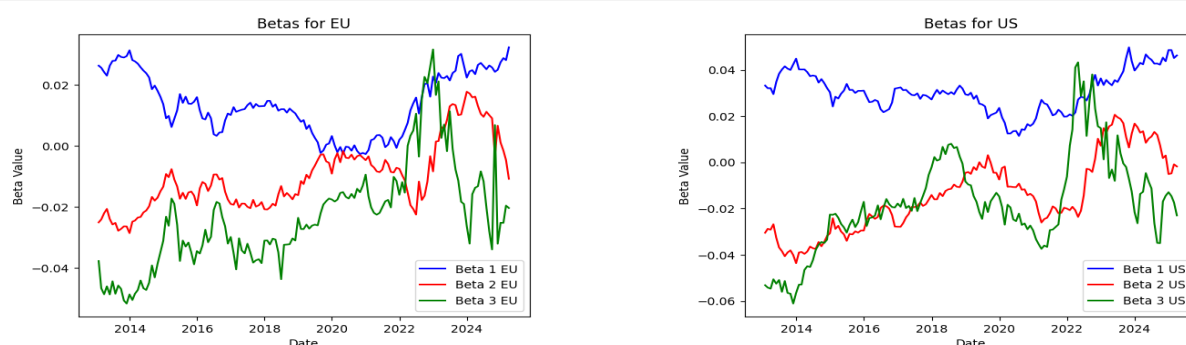
Statistical Metrics & Factor Diagnostics

Macro-Yield Curve Factor (Nelson-Siegel Betas)

Nelson–Siegel betas decompose the yield curve into three intuitive building blocks: β_1 – Level (parallel shifts up/down of all maturities). β_2 – Slope (steepening/flattening between short- and long-end rates) and β_3 – Curvature (hump-shaped twists centred on intermediate tenors). Monitoring their paths offers a quick, model-agnostic read-out of policy expectations and duration risk.

The level (β_1) component has trended lower in both blocs since mid-2023, thus signalling a broad repricing of long-term nominal rates. The slope factor (β_2) steepened sharply in the US after Q3-2023, while remaining near zero in the Eurozone, suggesting a stronger policy-rate guidance effect in the US. Curvature (β_3) oscillates around neutral in both cases.

Diverging slope dynamics imply that US duration exposure is more sensitive to policy surprises than its European counterpart; we therefore keep regional beta overlays un-hedged in the US leg only.

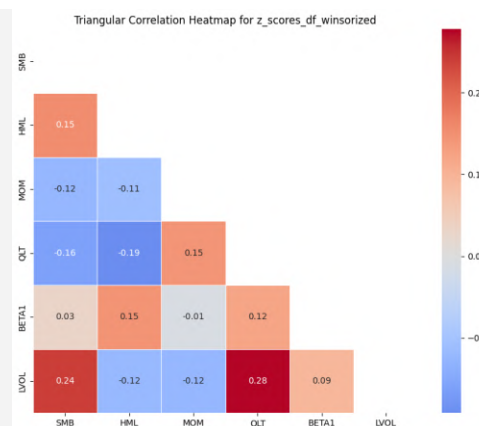


Cross-Factor Dependence

Pairwise correlations among the six style factors remain generally low, with no value exceeding ± 0.3 .

The strongest positive relationship is observed between Quality and Low Volatility ($\rho = +0.28$), highlighting the defensive nature of high-quality stocks, which tend to exhibit lower risk. Value and Momentum are negatively correlated ($\rho = -0.31$), consistent with their historically opposing behaviour. Size appears largely uncorrelated with other factors, notably showing near-zero correlation with Market Beta ($\rho = +0.03$) and only weak ties to Momentum and Quality, preserving its role as a diversifier.

Overall, the low degree of multicollinearity across factors supports the use of an equal risk contribution approach in portfolio construction.



	SW Statistic	p-value	$\sim \mathcal{N}$
SMB	0.9926	0.0000	No
HML	0.9970	0.0458	No
MOM	0.9922	0.0000	No
QLT	0.9927	0.0001	No
BETA1	0.9731	0.0000	No
LVOL	0.9978	0.1890	Yes

Distributional Checks & Normality

Descriptive statistics confirm that the factor scores are centered 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 behavior 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.

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Performance

The last portfolio allocation took place on November 22nd, 2024. Therefore, our timeframe is the five months and 3 days from November 22nd, 2024 to April 25th, 2025. Over this period, the portfolio obtained an absolute return of **€ 149.32** starting from **€ 100.000 of total exposure (0.35% annualized)** at the start date on the long and the short leg.

If we look at the cumulative performance starting from November 21, 2021, the inception of the fund, the portfolio generated a total return of **€40.438.52**. However, **more than 50%** of this sharp increase occurred in the first six months.

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.

In particular, over this semester the **best performer** was the **S&P 500 long-short leg**, which produced gains of **€ 177.03**. To compare, the **STOXX EUROPE 600 long-short leg** contributed with the significantly lower and even negative amount of **- €27.70**. After a strong finish in late 2024, the portfolio's performance dropped sharply at the start of 2025. February was particularly challenging with losses in both the STOXX Europe 600 and S&P 500 long-short positions. However, later that month a strong rebound allowed both legs to recover their losses, and the portfolio ended the first half of the year slightly above breakeven.

By diving more deeply, we can see that the **best performers** in the S&P 500 leg of the portfolio were **T Rowe Price Group Inc** (short, -30.79% over the period), followed by **NVIDIA Corp.** (short, -28.38%) and **Sapiens International Corp. NV** (short, -27.62%). The worst performers were instead **Delta Air Lines Inc.** (long, -39.74%), **American Airlines Group Inc** (long, -37.91%) and **United Airlines Holdings Inc.** (long, -34.43%). We can then say that the best performers were mainly represented by short position, while the worst performances by long positions.

Looking at the **STOXX Europe 600 leg**, the **best performances** come from **Leonardo** (long, +74.91% over the period), **Banco de Sabadell SA** (long, +51.44%) and **Bankinter** (long, +43.30%). The worst performers were instead **Glencore plc** (long, -31.68%), **Lifco AB** (short, +31.01%) and **Lagercrantz Group AB** (short, +26.53%). In this leg it is possible to observe an opposite trend with respect to the US one, with long position representing most of the best performances and short one the worst performances.

Overall, the fund has performed well, even if profits were modest given the period of uncertainty and market volatility. Moreover, the cumulative performance of the fund shows that a set of well selected investment factors has consistently yielded positive returns since the inception of fund.

Previous Allocation Performance in € (November 22, 2024 –April 25, 2025)



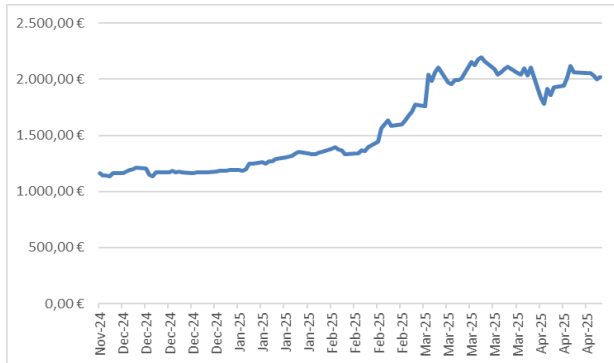
Source: Minerva Investment Management Society and Thomson Reuters Datastream. Past performance is not an indicator of future results.

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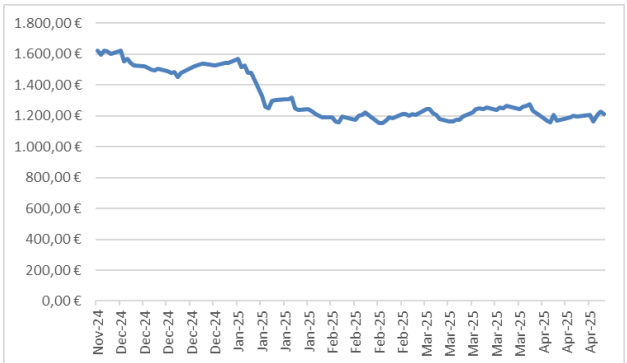
Top Performer: Leonardo (Long)



Leonardo S.p.A. is a leading European company specializing in the **design, manufacturing, and commercialization of aerospace and defense systems**. Its revenue is distributed across key product and service lines: **defense systems**; helicopters for both civil and military use; **aeronautical equipment**; space systems; aerostructures and other segments. Geographically, revenue was split as follows: **Italy** (18.2%), the UK (12.3%), Europe (26.4%), the U.S. (23.2%), and other regions (19.9%). The performance over the last six months has been fueled by **escalating geopolitical tensions**, coupled with the EU's ambitious **€800 billion** rearmament plan.

Source: LSEG Workspace . Total Return Index

Worst Performer: Delta Air Lines Inc. (Long)



Delta Air Lines. Inc. is a leading provider of passenger and cargo transportation services across the **United States and worldwide**. Through its extensive network of domestic and international code-sharing partnerships. Delta serves 264 cities in U.S. states and 230 international cities in 84 countries. The company's stock has underperformed in the last six months, reflecting broader **challenges in the airline industry**, including **volatile demand and high fixed costs**, which have pressured profitability across the sector.

Source: LSEG Workspace . Total Return Index

Cumulative Performance in € (November 21. 2021 – April 24. 2025)



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

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Improving the 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 — traits that offer 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.

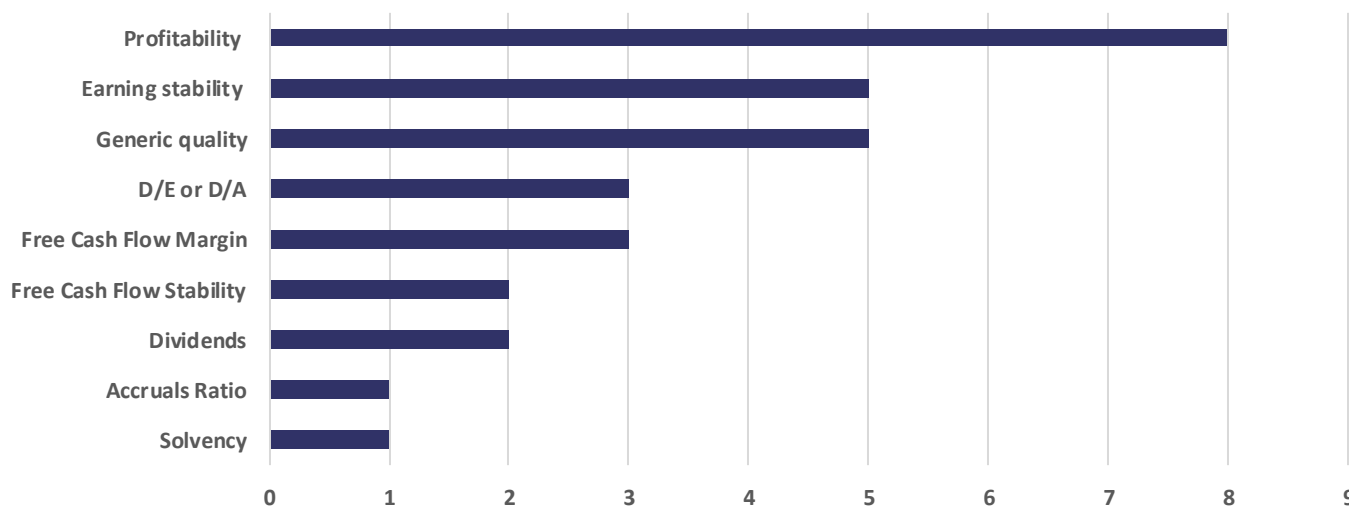


FIGURE 2: Usage of quality sub-factors amongst asset management firms

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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Improving the factor weightings

Before this adjustment, the fund primarily relied on the following strategy to determine the stock weights in the portfolio. After selecting the stocks using the discretionary factor weights, the corresponding portfolio weights were derived by normalizing the final scores assigned by the factor exposures. This strategy, although it provided a robust methodology to obtain portfolio weights since it reflected tactical beliefs and incorporated previous market research in fund allocation, can be potentially improved since it directly relies on factor weights and not rigorous portfolio optimization. In the portfolio optimization literature, there is voluminous research focusing on delivering the highest returns while at the same time minimizing variance, first proposed by *Bruno de Finetti (1940)* in the paper “*Il problema dei pieni*” and then introduced to the English literature by *Harry Markowitz (1952)* in the “*Portfolio selection*” paper. This idea lies at the core of the Modern Portfolio Theory and provides a straightforward way to create an optimal portfolio. The optimal portfolio, thus, maximizes the expected return of the portfolio:

$$E(R_p) = \sum_i w_i E(R_i)$$

And minimizes the portfolio return variance:

$$\sigma_p^2 = \sum_i \sum_j w_i w_j \sigma_{ij}$$

where w_i is the weight in the portfolio of the stock i , $E(R_i)$ is the expected return of the stock i , and σ_{ij} is the covariance between stock i and stock j .

One implementational consideration is that the expected return of the portfolio and portfolio return variance can be optimized in different ways depending on the investment objective. In our fund, as we aim to generate the highest risk-adjusted returns without investment, we combine the two objectives into one by using the Sharpe ratio. Therefore, the same problem can be equivalently stated as a choice of stock weights that maximize the Sharpe ratio:

$$S_p = \frac{E(R_p - R_f)}{\sigma_p}$$

Where R_p is the return of the portfolio, R_f is the risk-free rate, and σ_p is the portfolio return standard deviation.

The Mean-Variance Optimization (MVO) approach is widely used in portfolio management and has been applied to study the long-short portfolio allocation. The common way to adapt the MVO in the context of the net-zero investment strategy followed by the fund is to create two sub-portfolios that take long or short-only positions as described in “*A Mean-Variance Capital Asset Pricing Model for Long Short Equity Hedge Fund Portfolios*” by *David Hampton (2009)*. We proceed in the same way.

Given the stocks from the factor ranking, we create two portfolios for securities with positive and negative weights and then choose the stock weights that maximize (or in the case of short only portfolio minimize) the Sharpe ratio.

Although this method contradicts the logic of portfolio optimization using all assets in the investible universe, it is consistent with the fact that the underlying stocks are chosen using our model combined with the outlook on the market, and the optimization is undertaken in the last step to incorporate previous market evolution and minimize portfolio variance, which will improve the performance of the fund. Finally, although we apply the MVO framework, which is chosen because of its simplicity and flexibility to the fund, it has alternatives such as the Black-Litterman Model and Risk Parity approaches, which are more elaborate and aim to do the same final weights selection.

In particular, we have studied a more advanced Hierarchical Risk Parity (HRP) approach based on the probabilistic graph theory and machine learning methods. The main advantage of HRP is the ability to outperform MVO in predictive performance, which is exactly the aim of this fund. However, from the literature, as argued by *Marcos Lopez de Prado (2016)* in the paper “*Building Diversified Portfolios that Outperform Out-of-Sample*” the two methods (Critical line algorithm and HRP) do achieve similar portfolio variance (with the slight advantage of HRP) but HRP provides a robust method that does not rely on the invertibility of the variance-covariance matrix and therefore does not suffer from small changes in single asset volatility which is a major drawback of MVO. Additionally, HRP assigns more positive weights when compared to MVO, which makes it less exposed to idiosyncratic shocks, HRP was not used for this allocation since, to the best of our knowledge, there is no established literature on the application of the HRP to self-financing portfolios and no correct specification of the objective function for the short portfolios, which was done in the MVO approach. This method remains a possible improvement for our weight selection in the future.

Additionally, in portfolio management, there is an extensive literature on Markov switching models, which have been studied exhaustively (see “*Markov Switching Models in Empirical Finance*” *Massimo Guidolin (2012)*). We were interested in looking at Markov switching dynamic factor models. These models are applied to various problems in time series, macroeconomic monitoring, and forecasting. They are characterized using a Hidden Markov Model to first estimate the state and the transition probabilities and then use the obtained state distribution to estimate the dynamic factor models in each of those states. This model was introduced by *Diebold and Rudebusch (1996)*, and it allows inference of the latent factor from multiple observed variables and allows the dynamics of those factors to be regime-dependent using a hidden Markov process. This allows first to separate the data into different states where different factors may have opposite effects and then estimate the effect of those factors in each state.

Application of these models for factor weights optimization presents a direction for improvement of the fund. Nevertheless, to incorporate this class of models we must empirically estimate the joint distribution of all the states and factor portfolio returns used for the allocation. This task requires the computing capacity, empirical foundation, and academic research not available to us. Therefore, it only remains a theoretical model, not feasible for actual allocation.

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Quantitative Research Team

Risk Report – May 2025

Introduction

The main objective of this section is to assess and quantify the risk embedded in the Minerva IMS Long-Short Equity Fund built by the portfolio team. We use a daily perspective on the potential extreme behavior of a basket of assets selected by the portfolio analysts. The analysis will include three VaR and ES models (two parametric and one non-parametric) and an overview of how sentiment analysis can be considered a factor for short term investments.

As the Quantitative Research division, our focus is the estimation of the two main risk indicators:

- The daily Value at Risk (VaR): the maximum portfolio loss that occurs with $\alpha\%$ of probability over a time horizon of 1 day. For instance, if the VaR ($\alpha=5\%$) = -3.00%, it means that tomorrow there is a 5% probability of encountering a loss in the interval [-100%, -3.00%] potentially;
- The daily Expected Shortfall (ES): the expected return on the portfolio in the worst $\alpha\%$ of cases. So, it is just a mean of the returns lower than the VaR.

A simple technique to estimate these two measure is based on a historical approach: given a time series of returns of a financial security, we can easily compute the desired quantile of the historical distribution to estimate the VaR, and, after that, estimate the ES just by averaging the values below this threshold.

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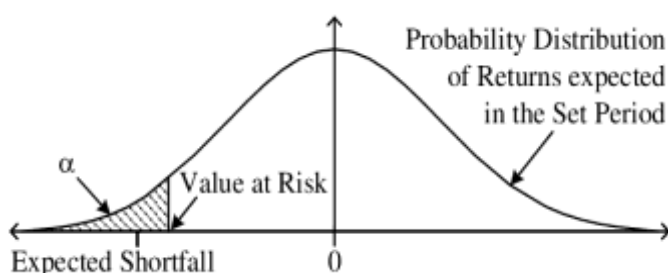
However, this naive approach is not well suited for our purpose: in fact, by considering our portfolio as a single financial asset, we are losing all the information that comes from all the components; moreover, with this approach we are simply focusing on the past behavior of the fund, while our main goal is to retrieve a risk metric for the future possible trends.

In order to overcome these issues, we propose two alternative techniques that provides better risk estimates:

- Parametric approach (simple approach and time-series modelling approach),
- Bootstrapping

The first method is very well suited for understanding the main vulnerabilities in the portfolio composition, while with the second one it is possible to observe how the metrics varied in the past quarters.

For both pieces of analysis we used daily market prices of portfolio constituents for the past 250 trading days. All the analysis has been conducted with Python.



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Parametric approach

In this section we propose to analyze VaR and ES separately for each asset included in the portfolio and then, to estimate the VaR and ES for the whole fund by taking into account the correlation between portfolio constituents.

Parametric approach is based on the assumption that returns of a financial security follow some theoretical distribution. Thus, VaR and ES can be expressed as an α -percentile of the distribution. The crucial step to accurately estimate VaR and ES is to select the appropriate distribution of returns and estimate its parameters.

It is possible to state that stock returns do not follow Gaussian distribution due to the presence of "fat tails": unexpected events might have a huge impact on the stock prices, so it is possible to observe extreme values more frequently than a Normal distribution would predict. For this reason, we assume that stock returns follow a Student-t distribution, thus, the parameters to be estimated are the mean μ , volatility σ and number of degrees of freedom ν .

To obtain more valid and robust results, we proceed with two alternative parameter estimation approaches – (a) simple approach, and (b) time-series modelling approach. For all parts of analysis, we use the last 252 return observations, which correspond to 1-year window.

Simple approach

Under the simple approach, we estimate the above-mentioned parameters in the following way:

1. We assume that the mean historical daily return of each security are a good estimate for the expected future return. Thus, μ is estimated as a simple average of daily returns.
2. Volatility of returns σ is calculated as a simple standard deviation of returns.

3. Number of degrees of freedom ν is selected in a way that it best approximates the empirical distribution of returns. In order to do that, we used the Kolmogorov-Smirnov statistic that, for a given empirical cumulative distribution function F and a proposal F_n , is:

$$D_n = \sup x |(F_n - F)|$$

Ideally it should be equal to 0 for a perfect fit, so our goal is to minimize it by proposing different ν for Student-t distribution.

Time-series modelling approach

Because the volatility of returns is not constant over time, it is often modelled by conditional heteroscedasticity processes. The most common way to model volatility is through a Generalized Autoregressive Conditional Heteroscedasticity model GARCH(p,q), where the forecast of the next-period volatility depends on the previous p shocks to stock returns (derived from some mean model) and previous q forecasts of volatility:

$$\sigma_{t+1|t}^2 = \omega + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j+1|t-j}^2$$

The advantage of GARCH model is that it allows to better estimate the current forecast of return volatility by putting more weight on more recent information. Thus, in the periods of market turbulence GARCH model will produce higher volatility forecasts than the simple average of squared deviations from the mean (see the graph at the bottom).

Because the portfolio is composed exclusively of equity instruments traded on liquid markets, we can assume that prices are efficient, and thus returns can be described by a constant mean model for GARCH(p,q) process, which implies that current mean estimates do not depend on previous returns or shocks. GARCH(p,q) then is estimated by Maximum Likelihood (MLE), which optimizes the distribution parameters. We subsequently use MLE estimates of distribution to derive VaR and ES.

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Parametric approach (continued)

Value-at-Risk

Once the parameters of stock returns are known, it is possible to calculate VaR. We estimate the VaR for 95% and 99% confidence level by applying the following formula:

$$VaR_{\alpha} = \sigma * T_{\nu}^{-1}(\alpha) + \mu$$

where σ is the estimated volatility of a security, $T_{\nu}^{-1}(\alpha)$ is the α -percentile of a Student-t distribution with ν degrees of freedom, and μ is the expected return of a stock.

Expected Shortfall

Expected shortfall is defined as a conditional expectation of loss, given that the loss occurred. If we introduce the assumption of a continuous distribution of returns of a security, then parametric expected shortfall is simply defined as a tail conditional expectation, and thus can in general be defined by the following formula for any security X :

$$ES_{\alpha}(X) = -\frac{1}{\alpha} \int_0^{\alpha} VaR_{\gamma}(X) d\gamma$$

Under the assumption of Student-t distribution with ν degrees of freedom it can be proven that the expected shortfall would be given as:

$$ES_{\alpha}(X) = \sigma * \frac{\nu + (T_{\nu}^{-1}(\alpha))^2}{\nu - 1} \frac{\tau_{\nu}(T_{\nu}^{-1}(\alpha))}{\alpha} + \mu$$

where σ is the estimated volatility of a security, $T_{\nu}^{-1}(\alpha)$ is the α -percentile of a Student-t distribution with ν degrees of freedom, $\tau_{\nu}(\cdot)$ is the probability density function of Student-t distribution with ν degrees of freedom and μ is the expected return of a stock.

We estimate the ES for 95% and 99% confidence level.

Portfolio VaR and ES

Considering the correlation between the stocks, we estimate the VaR and ES of the whole portfolio for 95% and 99% confidence level by applying the following formulas:

$$VaR_{\alpha,ptf} \approx \sqrt{VaR_{\alpha} * \rho * VaR_{\alpha}'} \\ ES_{\alpha,ptf} \approx \sqrt{ES_{\alpha} * \rho * ES_{\alpha}'}$$

where VaR_{α} and ES_{α} are column vectors of individual stock VaR and ES, respectively and ρ is the correlation matrix between securities

The approximation arises because of the assumption of Student-t distribution of returns – the formulas above become an equality the closer the distribution of returns is to the Gaussian.

	Simple approach	GARCH
VaR_{95%}	-1.07%	-1.42%
VaR_{99%}	-1.52%	-2.58%
ES_{95%}	-1.35%	-2.22%
ES_{99%}	-1.76%	-3.83%

TOP & BOTTOM 5 stocks (simple approach)

	VaR 95	VaR 99	ES 95	ES 99
GBLB.BR	-1.44%	-2.05%	-1.82%	-2.37%
ALLN.S	-1.64%	-2.32%	-2.06%	-2.67%
MMC.N	-1.68%	-2.38%	-2.11%	-2.74%
ITW.N	-1.70%	-2.41%	-2.14%	-2.77%
WLSNc.AS	-1.85%	-2.59%	-2.31%	-2.97%

	VaR 95	VaR 99	ES 95	ES 99
TOM.OL	-6.38%	-9.09%	-8.04%	-10.47%
MRNA.OQ	-6.67%	-9.64%	-8.49%	-11.15%
LPPP.WA	-7.26%	-10.35%	-9.16%	-11.94%
PAYC.N	-7.22%	-10.43%	-9.19%	-12.07%
ENR1n.DE	-8.11%	-11.43%	-10.15%	-13.12%

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Bootstrapping

When estimating a certain metric, one of the main problems in Statistics is the lack of the whole population data and the consequent use of only a sample. In our case the population data is the complete historical price data of the securities that are part of our portfolio, in which we only have the data of recent years.

Bootstrapping is a statistical technique that by having only a sample of the population data, provides estimates of statistical metrics that are closer to the ones obtained from the population data.

	Estimate	Standard error
VaR_{95%}	-1.09%	0.14%
VaR_{99%}	-1.88%	0.59%
ES_{95%}	-1.55%	0.22%
ES_{99%}	-2.40%	0.62%

Given a sample of size n , implementing bootstrap is very simple:

- Sample with replacement n times from the original sample (note that one observation could be selected more than once);
- Compute the metric of interest (in our case the VaR or ES) on this newly created sample and save it;
- Repeat the previous steps M times with $M \rightarrow +\infty$ (we have selected $M=100.000$ for instance);
- Average and compute the standard error of the metrics estimated in each step.

With this method, by estimating the expected shortfall and the standard errors, we can retrieve a more insightful view of our portfolio, but in this case, we are losing the risk contribution of each stock that we had in the previous case.

TOP & BOTTOM 5 stocks (GARCH)

	VaR 95 (GARCH)	VaR 99 (GARCH)	ES 95 (GARCH)	ES 99 (GARCH)
GBLB.BR	-1.46%	-2.20%	-1.92%	-2.66%
ALLN.S	-1.88%	-2.91%	-2.53%	-3.62%
ITW.N	-1.97%	-3.08%	-2.67%	-3.85%
EMSN.S	-2.13%	-3.25%	-2.83%	-3.98%
WLSNc.AS	-2.11%	-3.40%	-2.95%	-4.42%

	VaR 95 (GARCH)	VaR 99 (GARCH)	ES 95 (GARCH)	ES 99 (GARCH)
NCLH.N	-9.12%	-17.66%	-15.11%	-27.59%
MRNA.OQ	-9.26%	-17.88%	-15.21%	-27.34%
ENR1n.DE	-10.92%	-20.24%	-17.34%	-30.31%
TOM.OL	-12.30%	-25.35%	-21.75%	-42.39%
SMCLOQ	-19.10%	-39.69%	-34.08%	-66.99%

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