

MIMS – Long-Short Equity Fund

Portfolio Management Team

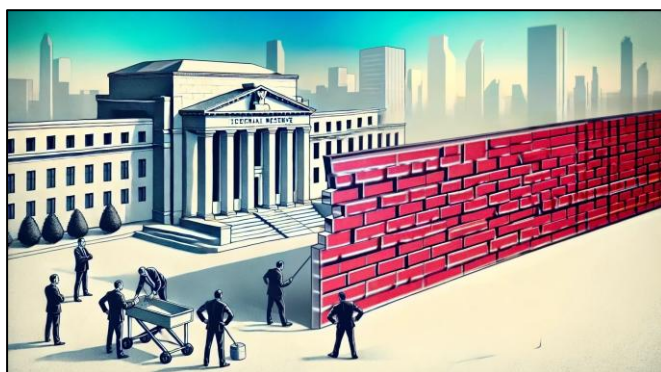
Report – December 2024

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, Trump's victory in the elections with a Republican sweep will probably imply significant policy shifts. Key proposals include strict immigration laws, increased domestic production of oil and gas, broad deregulation, and a sharp cut of corporate tax from 21% to 15%. The most discussed policy would be a 60% tariff on China and a 10% base tariff on imported goods, which could ignite a trade war. In Europe, Germany's governing coalition collapsed after Chancellor Scholz dismissed the finance ministry. The political instability could emphasize the economic hardship Germany is facing, lagging behind other European economies with a 0.1% GDP decline this year and a slim forecasted growth of 0.7% for 2025 combined with a struggling automotive sector.
- In the last six months, the Federal Reserve interest rates gradually dropped from 5.5% to 4.75%, aiming for a soft landing. However, possible inflation expectations remain, and the Federal Reserve may opt for a more conservative approach in cutting rates due to higher-than-normal inflation expectations caused by Trump tariff policies. The ECB has followed through with a similar interest rate cut, with MRO going from 4.5% to 3.4% over the last six months.
- In Europe, the HICP rose 2.0% YoY in October in the Euro area, on track to reach the ECB medium-term 2% inflation target. In the US, the CPI rose 2.6% in October YoY and 0.2% from September, while Core CPI increased 3.3% YoY, gaining 0.3% relative to September.
- Markets face significant volatility as investors weigh the impact of political uncertainty. The shadow of an impending trade war looms over Europe, and the trade policy uncertainty itself could cause significant growth drag. The current outlook for the coming years has driven up long-term US bond yields and further strengthened the Dollar against the Euro, with investors anticipating a spread of US rates against EU ones.



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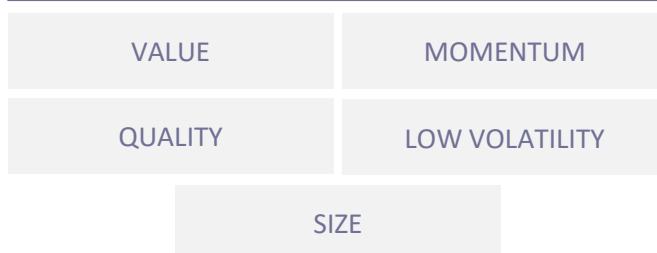
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Factor Investing Strategy



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 semester. 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 was refined with several enhancements, including sector-specific winsorization and the development of a new safety factor.

The model is based on a five-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)) and idiosyncratic volatility (IVOL, Ang, Hodrick, Xing, and Zhang (2006)). Explanations of each factor can be found under "Fund Factors".

Each factor is 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, typically 5 or 10 in number. 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.

Following a style-analysis approach, we regress each stock in our investable universe on our 5 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. The final portfolio consists of 20 stocks in each segment (long/short, EU/US). The qualitative checks are discussed in further details at the end of the "Tactical Decision" section. The weights of the selected stocks are normalized so that the weights in the long leg sum to 1 and those in the short leg also sum to 1. Consequently, the overall portfolio weight sums to zero. The above-mentioned mechanism enables the fund to take more significant positions in companies with higher model-derived scores (and vice versa for short positions).

Fund Factors

Value Factor – Long position

- The value factor is now based on the High-Minus-Low (HML) factor of Fama & French (1992, 1993). The factor exposure is then calculated as the beta towards this factor portfolio in a full 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 remain stable in the future and will be a reliable driver of future increases in stock prices.
- 5y growth in ROE: to account for the growth of companies, 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 financial stability.
- 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).

Size Factor – Short position

- SMB factor based on Free-Float Market Capitalization (Fama & French, 1992, 1993): over time, 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), 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

Based on insights from academic research (page 7), a higher weight has been assigned to the value factor (HML) by reducing the allocation to momentum (MOM). This adjustment aims to capture undervalued companies while exiting positions in overvalued ones. In the context of potential disruptive changes over the next six months, this factor is expected to generate sustainable returns on both legs.

Additionally, the short position on the SML (size) factor has been reduced to 5%. While large companies are considered relatively more valuable than small ones in uncertain conditions, it is acknowledged that a low absolute weight for this factor will have minimal impact on the overall portfolio allocation. At the same time, a completely neutral position was avoided to capitalize on the relative stability offered by large-cap stocks. Overall, given the weaker empirical support for the -reversed-SMB effect, the short position has been adjusted closer to neutrality.

However, the most important change involved the elimination of the earnings quality factor and the creation of the payback period factor. Earnings quality, though interesting, proved complex to calculate and incompatible with the Python model. Instead, a more practical multiple from the Ohlson score (see page 8) was chosen. Combined with a 25% increase in the equally weighted quality factor, this highlights a focus on solid companies capable of delivering consistent returns in uncertain or low-growth conditions. The Low Idiosyncratic Volatility factor remains at 30%, serving both as a risk-budgeting tool and a defensive strategy against potential market disruptions following Trump's inauguration.

Portfolio weights are calculated using a score-based methodology, normalized to sum to one per region. To ensure industry neutrality, overrepresented sectors are balanced by substituting companies with higher (long-leg) or lower (short-leg) scores from underrepresented sectors, as illustrated in the accompanying bar chart. This adjustment, guided purely by scoring, achieves semi-sector neutrality without subjective stock-picking.

Factor weights

Value (25%)	High-Minus-Low Book-to-Market (HML) Factor	25%
Inverted Size (5%)	Small-Minus-Big Market Capitalization	5%
Momentum (15%)	Carhart (1997) Momentum	15%
Quality (25%)	Profitability: ROE	6.25%
	Growth: ROE 5y growth	6.25%
	Debt to Equity	6.25%
	Safety Factor: Payback Period	6.25%
Low Volatility (30%)	Standard deviation of idiosyncratic errors from factor model	30%

New Fund Positioning

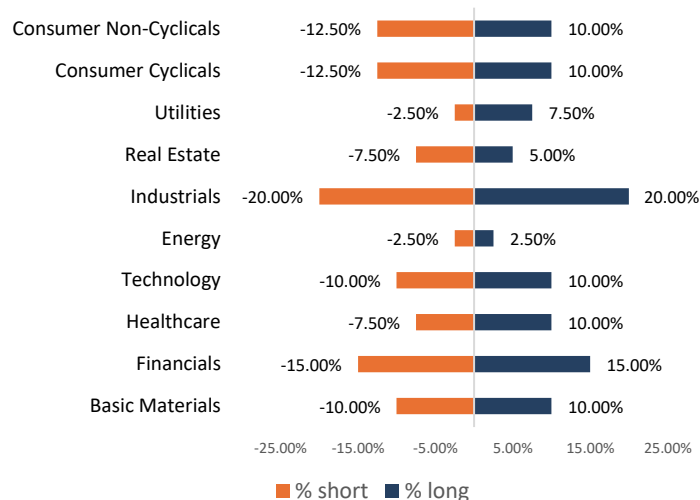
S&P500			
KENVUE INC	1.817	ROCKWELL AUTOMATION INC	-1.136
CF INDUSTRIES HOLDINGS INC	1.168	DOVER CORP	-1.131
		MARSH & MCLENNAN COMP INC	-1.055
UNITED AIRLINES HOLDINGS INC	1.160	ILLINOIS TOOL WORKS INC	-1.048
PG&E CORP	1.119	AMAZON.COM INC	-1.007
DELTA AIR LINES INC	1.056	T ROWE PRICE GROUP INC	-1.003
MOSAIC CO	0.995	APTIV PLC	-0.983
AES CORP	0.899	COSTCO WHOLESALE CORP	-0.980
SOUTHWEST AIRLINES CO	0.800	ANSYS INC	-0.965
KIMCO REALTY CORP	0.784	INVITATION HOMES INC	-0.936
PARAMOUNT GLOBAL	0.773	BLACKROCK INC	-0.928
HUNTINGTON INGALLS IND INC	0.736	SYNOPSIS INC	-0.908
INSULET CORP	0.717	ECOLAB INC	-0.904
KRAFT HEINZ CO	0.713	AMETEK INC	-0.894
AKAMAI TECHNOLOGIES INC	0.706	TE CONNECTIVITY LTD	-0.886
AMERICAN AIRLINES GROUP INC	0.675	DANAHER CORP	-0.871
BUNGE GLOBAL SA	0.654	NVIDIA CORP	-0.838
VENTAS INC	0.652	CADENCE DESIGN SYSTEMS INC	-0.833
ABBVIE INC	0.622	ALIGN TECHNOLOGY INC	-0.761
BATH & BODY WORKS INC	0.612	EQUINIX INC	-0.738
FIDELITY NATIONAL INF S INC	0.554		
STOXX EUROPE 600			
TUI N (LON)	2.915	NIBE INDUSTRIER	-1.123
SANDOZ GROUP	1.979	LIFCO B	-1.118
AIXTRON (XET)	1.512	LAGERCRANTZ GROUP B	-1.046
INDIVIOR	1.421	INVESTOR B	-1.022
SSP GROUP	1.403	PARTNERS GROUP HOLDING	-0.996
BPER BANCA	1.399	GIVAUDAN 'N'	-0.953
BANCO DE SABADELL	1.341	SNAM	-0.945
FORTUM	1.337	CHOC.LINDT &SPRUENGLI PAR	-0.907
AIB GROUP	1.309	ALLREAL HOLDING	-0.900
OCI	1.292	NESTLE 'N'	-0.894
LEONARDO	1.284	VAT GROUP	-0.892
DSM FIRMENICH	1.273	THULE GROUP	-0.861
STANDARD CHARTERED	1.247	TOMRA SYSTEMS	-0.854
BANKINTER 'R'	1.213	KION GROUP (XET)	-0.849
UBISOFT ENTERTAINMENT CAT A	1.165	LATOUR INVESTMENT B	-0.751
ROLLS-ROYCE HOLDINGS	1.164	IMCD GROUP	-0.741
CAIXABANK	1.147	GEBERIT 'R'	-0.716
ACCELERON N	1.115	SIKA	-0.711
GLENCORE	1.118	LONZA GROUP	-0.683
FRONTLINE (OSL)	0.957	TERNA RETE ELETTRICA NAZ	-0.629

Score Long

Score Short

Score Long Score Short

Industries Breakdown



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Neutrality Hedges

As last semester, the fund meticulously follows a hedging strategy. Given the companies in our proposed portfolio allocation, we achieved a significantly reduced beta compared with last semester's beta.

For the European leg of the portfolio, the 10 year historical beta using monthly observations has been -0.09. For the US leg, the raw monthly beta has been -0.04. We observe that there is no a significant difference between the US beta and the EU beta as we witnessed last semester.

In this semester we conclude that our betas are not statistically significant and as 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 stay neutral to the underlying movements in the indices.

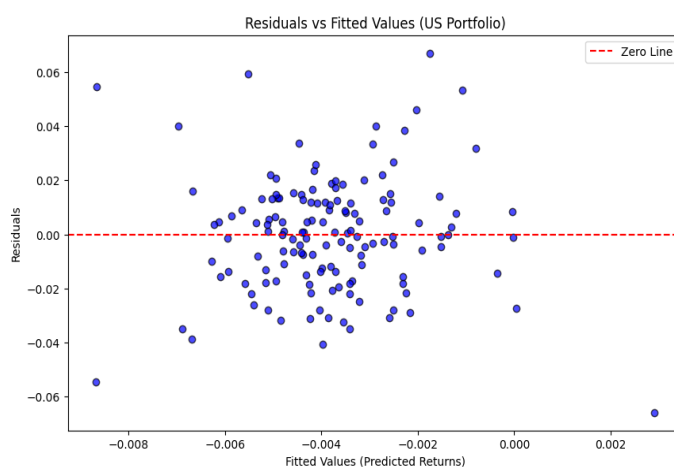
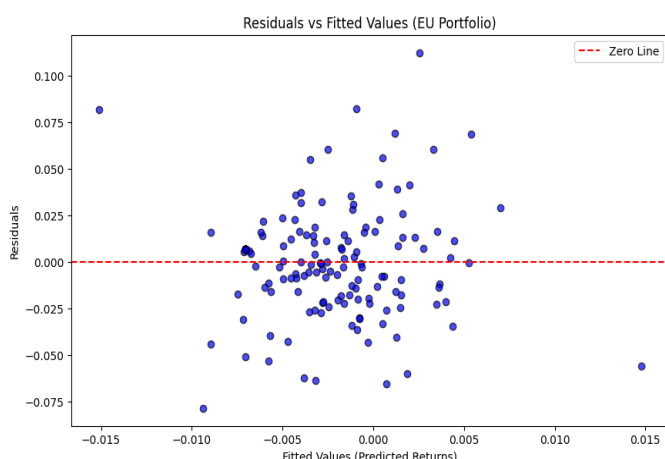
It is important to note that beta exposures are subject to change over time, which could result in significant variations in the portfolio's beta within weeks or months. Maintaining a consistently beta-neutral position would require dynamic hedging with futures on the underlying indices. However, this 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:	0.017	
Model:	OLS			Adj. R-squared:	0.010	
Method:	Least Squares			F-statistic:	2.536	
Date:	Mon, 25 Nov 2024			Prob (F-statistic):	0.113	
Time:	09:25:59			Log-Likelihood:	313.66	
No. Observations:	149			AIC:	-623.3	
Df Residuals:	147			BIC:	-617.3	
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-0.0009	0.003	-0.333	0.740	-0.006	0.004
STOXX Europe 600	-0.0924	0.058	-1.592	0.113	-0.207	0.022
Omnibus:	13.286	Durbin-Watson:	1.912			
Prob(Omnibus):	0.001	Jarque-Bera (JB):	20.583			
Skew:	0.466	Prob(JB):	3.39e-05			
Kurtosis:	4.564	Cond. No.	23.9			

OLS Regression Results						
Dep. Variable:	US Portfolio Returns			R-squared:	0.006	
Model:	OLS			Adj. R-squared:	-0.001	
Method:	Least Squares			F-statistic:	0.8108	
Date:	Mon, 25 Nov 2024			Prob (F-statistic):	0.369	
Time:	09:18:02			Log-Likelihood:	342.08	
No. Observations:	141			AIC:	-680.2	
Df Residuals:	139			BIC:	-674.3	
Df Model:	1					
Covariance Type:	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]
const	-0.0034	0.002	-1.801	0.074	-0.007	0.000
S&P 500	-0.0362	0.040	-0.900	0.369	-0.116	0.043
Omnibus:	5.095	Durbin-Watson:	1.564			
Prob(Omnibus):	0.078	Jarque-Bera (JB):	5.956			
Skew:	0.213	Prob(JB):	0.0509			
Kurtosis:	3.912	Cond. No.	22.2			



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Performance

The last portfolio allocation took place on April 30th 2024. Therefore, our timeframe is the six months and 22 days from April 30th 2024 to November 22nd 2024. Over this period, the portfolio obtained an absolute return of **€ 3162.29** starting from **€ 100,000 of total exposure (5.67% 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 **€ 40289.23**. 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 **€ 2015.15**. To compare, the **STOXX EUROPE 600 long-short leg** contributed with the significantly lower amount of **€ 134.89**. The months of September and October were challenging, with the fund experiencing significant negative returns especially due to the poor performance of the STOXX EUROPE 600 long-short leg. However, in November a strong positive performance trend occurred and both legs managed to end the semester with positive returns.

By diving more deeply, we can see that the **best performers** in the S&P 500 leg of the portfolio were **United Airlines** (long, +90.08% over the period), followed by **Insulet Corp.** (long, +57.06%) and **Gilead Sciences Inc.** (long, +45.09%). The worst performers were instead **Arista Networks Inc.** (short, +62.72%), **Synchrony Financial** (short, +54.10%) and **Walgreens Boots Alliance Inc.** (long, -46.40%). We can then say that the best performers were mainly represented by long position, while the worst performances by short positions.

Looking at the **STOXX Europe 600 leg**, the **best performances** come from **OCI** (long, +58.97% over the period), **Standard Chartered** (long, +42.26%) and **Pearson** (long, +30.45%). The worst performers were instead **Siemens Energy** (short, +152.69%), **Hellofresh** (short, +63.24%) and **Ubisoft Entertainment**. (long, -42.63%).

We can see the same picture as for the other leg, with long position representing most of the best performances and short one the worst performances

Overall, the fund has performed well in a period of uncertainty and volatility and 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.

The (long) beta hedges added a total return of **€ 1012.25**, the great majority of which comes from the S&P 500 that experienced a more significant growth than the STOXX EUROPE 600.

Previous Allocation Performance (April 30, 2024 – November 22, 2024)



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

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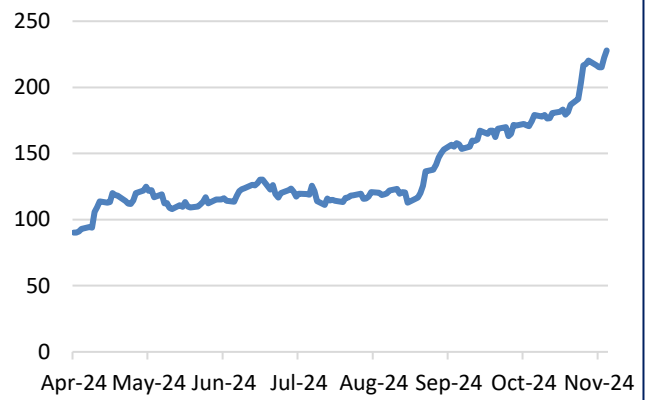
Top Performer: OCI N.V (Long)



OCI N.V. is a producer and distributor of natural gas-based **fertilizers** and **industrial chemicals** based in the Netherlands. Its product portfolio includes nitrogen fertilizers and industrial chemicals such as ammonia hydrate and methanol. Its subsidiaries include Biomethanol Chemie Nederland BV, focused on **bio-methanol production**. OCI primarily serves agricultural and industrial customers, with production sites in the Netherlands, the U.S., Egypt, and Algeria. A significant part of these returns is due to an **extraordinary dividend** distribution, following the completion of the sale of Iowa Fertilizer Company LLC (one of its subsidiaries)

Source: Refinitiv, Total Return Index

Worst Performer: Siemens Energy AG (Short)



Siemens Energy AG is a global leader in **energy technologies**. The company provides a wide range of products and services related to energy generation, transmission, and storage

Siemens Energy has shown strong performance during the past 6 months. The company returned to profitability, posting a FY **profit of 345 mln euros** after a previous year loss of 2.8 bn euros. This recovery is driven by streamlining operations. The company has also refocused its wind energy division on key markets such as Europe and the U.S.

Source: Refinitiv, Total Return Index

Cumulative Performance (November 21, 2021 – November 22, 2024)



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

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While momentum strategies tend to perform very well in stable/trending markets, they face significant challenges in periods of heightened volatility, as demonstrated in studies like “Momentum has its moments” (Barroso and Santa-Clara, 2015). Their research highlights that momentum strategies are particularly vulnerable to sharp reversals during volatile market conditions (Figure 1).

Market volatility often disrupts the trending patterns on which momentum strategies rely, making it difficult for such strategies to generate consistent returns. Abrupt reversals can quickly erode gains, creating a high-risk environment for momentum-driven approaches.

Given our forecast of elevated market uncertainty over the next six months, we anticipate that momentum may struggle to deliver a strong performance.

This concern is further amplified by our 6-month rebalancing constraint, which limits our ability to adapt quickly to shifting market trends. In fact, Barroso and Santa-Clara also proved how managing exposure to volatility can significantly enhance performance. Without the ability to adjust momentum exposures dynamically or frequently, portfolios remain more exposed to the risks of trend reversals and heightened volatility, undermining the effectiveness of momentum strategies under such conditions.

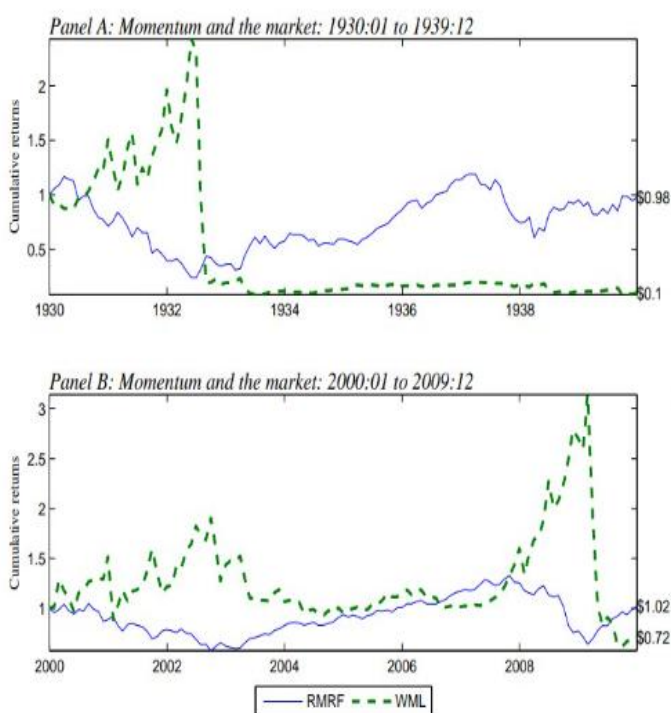


Figure 1: Momentum crashes

Source: Barroso and Santa-Clara, 2015.

The figure plots the cumulative return and terminal value of the momentum and market portfolio strategies in its two most turbulent periods: the 1930s and the 2000s.

- RMRF = market risk factor.
- WML = winners minus losers.

This thesis is further reinforced by “Another look at value and momentum: volatility spillovers” by Grobys and Vähämaa (2020).

The paper, while confirming that momentum strategies face notable challenges under volatile market conditions, also asserts that value strategies tend to excel during such periods. Their findings indicate that heightened volatility spillovers⁽¹⁾—often associated with broader market uncertainty—create conditions where value strategies outperform (see Figure 2).

This outperformance stems from the fundamentally driven nature of value investing, which focuses on companies with solid financial metrics and undervalued stock prices.

Unlike momentum, which is more susceptible to abrupt reversals in trends, value strategies benefit from the intrinsic stability of undervalued assets. These assets often rely on tangible financial health and cash flow resilience, allowing them to better weather turbulent market conditions and even capitalize on market corrections as prices revert to intrinsic values.

The historical performance of the value factor has indeed proven resilient during periods of market uncertainty, largely due to the above mentioned “mean reversion” effects.

In light of these considerations, the portfolio is being adjusted by lowering the momentum factor's weight from 20% to 15% and adding 5% to the value factor. The goal is to better match anticipated market conditions while keeping the rebalancing process practical.

(1) “Volatility Spillover” refers to the transmission of volatility between different investment strategies or asset classes, where shocks in one strategy (e.g., momentum) affect the volatility of another (e.g., value), especially during periods of market instability.

	Value	Momentum	Market index	Market volatility	Recession
VSPC	0.01	-0.02	0.02	0.02	-0.12
Value		-0.39	0.10	0.00	0.02
Momentum			-0.11	-0.11	-0.10
Market index				0.06	-0.10
Market volatility					0.25

Figure 2: Correlation coefficients

Source: Grobys and Vähämaa, 2020.

The table reports correlation coefficients between six different time-series over the period 1931–2015.

VSPC is the first principal component of three volatility spillover indices between the value and momentum factor portfolios with different lag-orders ($p = 2, 4, \text{ or } 6$).

Value is the monthly return for the value factor portfolio.

- Momentum is the monthly return for the momentum factor portfolio.

- Market index is the monthly excess return on the market index.

- Market volatility is the monthly stock market volatility based on a GARCH(1,1)

model, and Recession is a dummy variable that equals one during National Bureau of Economic Research recessions.

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Improving the Quality Factor

Building on the insights from Quality Minus Junk (Asness, Frazzini, and Pedersen, 2017), we are enhancing the traditional Quality factor by incorporating another Safety component, measured using the Payback Ratio. This ratio estimates the number of years it would take to repay total liabilities using cash generated from operating activities.

In the original paper, various additional metrics are employed to assess a company's safety, some of which we have chosen not to use, such as low Beta, and others, like leverage, are already integrated into our assessment. To further refine the Safety factor, we have decided to add a component related to bankruptcy risk—an element that was previously missing from the framework. This addition helps us more accurately measure financial stability, ensuring that we capture the full spectrum of risk (Figure 2).

A low Payback Ratio is highly desirable, as it indicates that the company generates strong cash flow relative to its liabilities, making it more capable of handling debt and investments. Conversely, a negative Payback Ratio signals negative operating cash flow, suggesting that the company may face challenges in covering its liabilities and investments, warranting closer scrutiny. In such cases, the stock is penalized in the factor's assessment. This enhancement supports the broader thesis that high-quality stocks—those that are profitable, growing, well-managed, and financially secure—deliver superior risk-adjusted returns, especially during periods of market uncertainty (Figure 3).

This new Safety element aligns with the broader thesis of the paper: solid companies are rewarded based on metrics like the Z-score and O-score. Notably, the O-score incorporates the Payback Ratio in its formula (Figure 1), providing a robust assessment of financial stability. While not perfect, this model predicts approximately 90% of bankruptcies within a two-year horizon, making it highly reliable for our fund. By focusing on these metrics, we effectively capture the "flight to quality" dynamic during periods of market turbulence, strengthening the portfolio's resilience in challenging environments.

Moreover, the decision of increasing the Quality factor was further supported by the strong performance of a similarly constructed factor compared with the 4-factor model, as illustrated in Figure X+2, showcasing its potential for generating consistent and robust returns.

$$\text{Liabilities Payback Period} = \frac{\text{Total Liabilities}}{\text{FCFO}}$$

FIGURE 1: Liabilities Payback Period Formula

Source:

The payback ratio is crucial in the Ohlson O-Score formula as it directly measures whether a company generates enough cash to cover its investments and liabilities. It is a key starting point in assessing financial health, as it highlights the company's ability to meet its financial obligations through operational cash flow. While it's part of the broader model, this ratio is foundational for understanding a company's liquidity and solvency.

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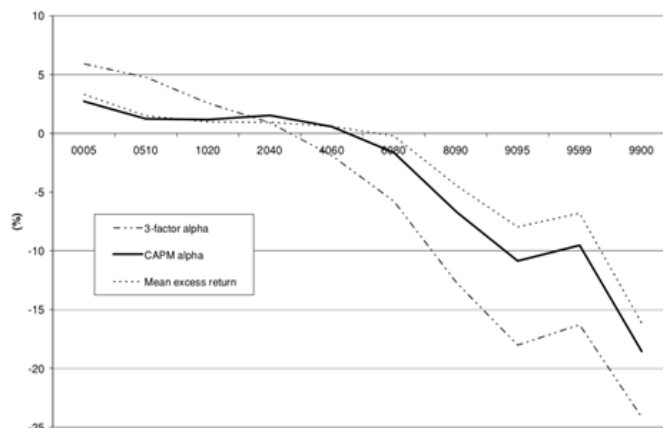


FIGURE 2: Returns of Distressed Stock Portfolios Sorted by Failure Probabilities

Source: Campbell, J. Y., Hilscher, J., & Szilagyi, J. (2008). In Search of Distress Risk. *Journal of Finance*, 63(6), 2899-2939.

The figure depicts the annualized mean excess returns, CAPM alpha, and Fama-French three-factor alpha for ten portfolios ranked by financial distress risk from 1981 to 2003. Financial distress is determined using failure probabilities estimated via a logit regression of predictor variables, based on bankruptcy data spanning 1963–1998. The results demonstrate that as financial distress risk increases, equity returns decline, illustrating the low returns associated with distressed stocks despite their higher risk.

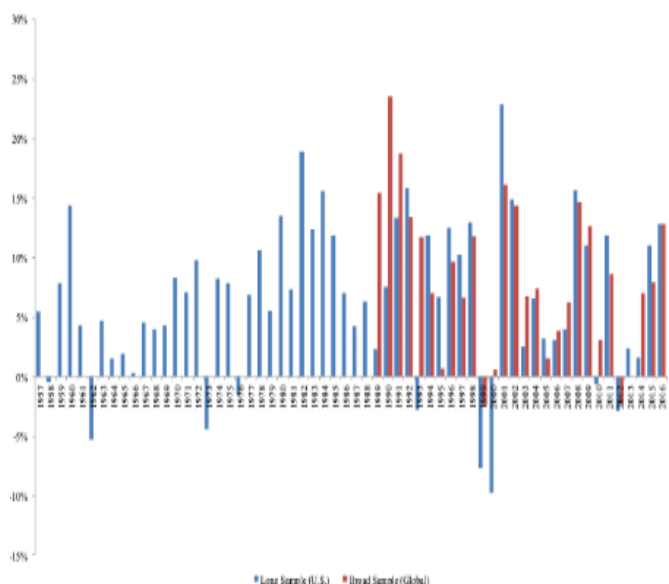


FIGURE 3: 4-Factor Adjusted Performance of Quality Minus Junk (QMJ) Across Regions

Source: Asness, Cliff S. and Frazzini, Andrea and Pedersen, Lasse Heje, Quality Minus Junk (June 5, 2017).

The figure shows 4-factor adjusted information ratios for Quality minus Junk (QMJ) factors across regions, using annualized alphas from time-series regressions. Returns are in USD (not currency-hedged), and excess returns are over U.S. Treasury bills. Size breakpoints differ by region, and performance is adjusted for market, size, book-to-market, and momentum factors.

Quantitative Research Team

Risk Report – December 2024

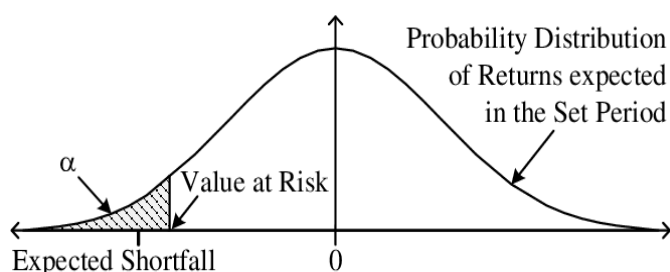
Introduction

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 6 months,. All the analysis has been conducted with Python.

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

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%}	-1.87%	-2.34%
VaR_{99%}	-2.70%	-4.13%
ES_{95%}	-2.38%	-3.54%
ES_{99%}	-3.14%	-5.85%

TOP & BOTTOM 5 stocks (simple approach)

	VaR 95	VaR 99	ES 95	ES 99
ALLREAL	-1.36%	-1.97%	-1.74%	-2.28%
MARSH&MCLENNAN	-1.50%	-2.16%	-1.91%	-2.50%
ILLINOIS TOOL	-1.57%	-2.26%	-2.00%	-2.62%
TERNA	-1.74%	-2.51%	-2.22%	-2.93%
INVESTOR AB	-1.73%	-2.53%	-2.22%	-2.94%

	VaR 95	VaR 99	ES 95	ES 99
NVIDIA	-4.95%	-7.25%	-6.36%	-8.43%
AIXTRON	-5.68%	-8.02%	-7.12%	-9.24%
TOMRA	-5.59%	-8.09%	-7.13%	-9.38%
PARAMOUNT	-6.00%	-8.55%	-7.57%	-9.86%
UBISOFT	-6.43%	-9.15%	-8.10%	-10.58%

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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.

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.

	Estimate	Standard error
VaR_{95%}	-1.82%	0.12%
VaR_{99%}	-2.87%	0.39%
ES_{95%}	-2.36%	0.22%
ES_{99%}	-3.13%	0.31%

TOP & BOTTOM 5 stocks (GARCH)

	VaR 95 (GARCH)	VaR 99 (GARCH)	ES 95 (GARCH)	ES 99 (GARCH)
MARSH&MCLENNAN	-1.72%	-3.00%	-2.55%	-4.06%
BLACKROCK	-1.93%	-2.97%	-2.58%	-3.59%
INVESTOR AB	-1.80%	-3.05%	-2.60%	-4.02%
ILLINOIS TOOL	-1.91%	-3.02%	-2.61%	-3.77%
TERNA	-1.95%	-3.02%	-2.62%	-3.72%

	VaR 95 (GARCH)	VaR 99 (GARCH)	ES 95 (GARCH)	ES 99 (GARCH)
AMERICAN AIRLINES	-6.49%	-12.18%	-10.39%	-18.24%
TOMRA	-7.19%	-13.74%	-11.73%	-20.99%
PARAMOUNT	-7.26%	-13.85%	-11.83%	-21.24%
UBISOFT	-8.80%	-18.93%	-16.39%	-33.67%
INDIVIOR	-13.17%	-28.75%	-24.92%	-51.84%

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