MIMS – Long-Short Equity Fund

Portfolio Management Team

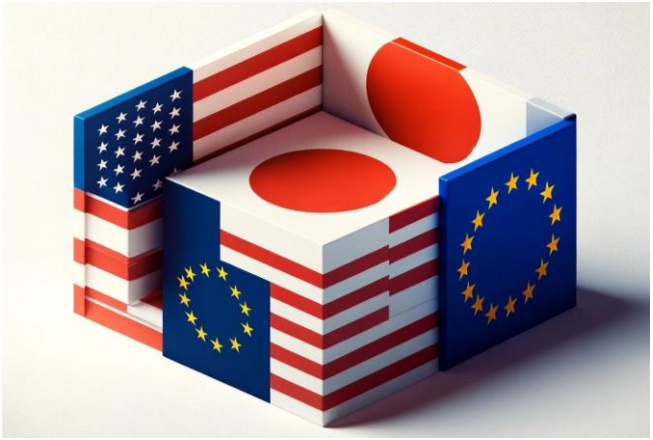
Report – December 2023

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 Federal Reserve kept the target range for the federal funds rate at its 22-year high of 5.25%-5.5%, for the second consecutive time in November. In Europe, the interest rates remain in a range between 4.00% and 4.75%. Both the US and European policymakers are committed to bring inflation down to the 2% target over the medium term to preserve the economy, therefore the rates are expected to remain "higher for longer", even if markets are already pricing in rates' cuts in the next months.
- October inflation data highlighted downward trends both in the US and in Europe. On the other hand, according to the ECB, the anticipated median inflation for the next 12 months increased to 4.0% in October, from 3.5% and 3.4% in August and July, respectively. The forward 3 years expected inflation was kept at 2.5%, showing how the end in monetary tightening has not impacted the long-term forecasts, unleashing increasing uncertainty for the next years.
- The Bank of Japan seems committed to its Yield Curve Control (YCC) monetary policy, despite a stagnant economy and persistently high inflation. In response to extraordinarily high yields and historically weak yen, the central bank decided to include substantial bond purchase programs and remove the 1% cap on the 10-years bond yields.
- During the last six months, the US markets have collected positive returns, further pushed by the AI race: the S&P 500 index and the Nasdaq Composite index gained respectively 8.22% and 10.43%. European performance has been most affected by international tensions and oil prices: the STOXX EUROPE 600 index recorded a 1.83% gain over the last semester. In Asia, the Nikkei 225 gained 6.05% during the same period, thanks to government policies and low rates. Oil price is declining to the lowest levels since July 2023, however, it is expected to increase in 2024 due to the recent announcements of production cut by OPEC.



Head of Asset Management
Jacopo Prevedello: jacopo.prevedello@studbocconi.it

Head of Portfolio Management
Matteo Consalvo: matteo.consalvo@studbocconi.it

Portfolio Manager
David Overbeck: david.overbeck@studbocconi.it

Portfolio Analysts
Michele Rinaldi: michele.rinaldi@studbocconi.it
Anna Maruccio: anna.maruccio@studbocconi.it
Erik Vik: erik.vik@studbocconi.it

Factor Investing Strategy

VALUE	MOMENTUM
QUALITY	VOLATILITY
SIZE	ESG

3 Steps Investment Approach

Multi Factor Analysis

Fundamental metrics are identified that best proxy each of the 6 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 3-step 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).

A score is produced with reference to each considered style factor: (1) 'value' (stocks with lower price-to-book ratio and lower EV/FCF than peers); (2) 'size' (in terms of free-float market cap); (3) 'momentum' (investments with relatively strong recent performance); (4) 'quality' (as reflected by indicators such as ROE, ROE 5y growth, D/E and Earnings quality); (5) 'low idiosyncratic volatility'; (6) 'ESG' factor (as conveyed by the Thomson Reuters ESG Score). 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. Each factor is given a specific weight in the process of building a final score for each stock. Sector-neutrality is considered.

Tactical Decisions

In rebalancing the previous portfolio and building the new one, we adopted significant changes. **We reviewed the value factor**, redefining both metrics that compose it (see page 6 for details) to account for the increase in off balance sheet assets in recent years. **We keep the individual weights for each factor** to express strong factor opinions where we have significant macroeconomic convictions. In addition, **we introduced score-based weights within our portfolio**. Therefore, stocks that have higher exposure to our factor selection will be overweight in the portfolio and stocks that have lower exposure but are still selected in the portfolio will be underweight. Next, **we made our portfolio beta neutral in both regions** by going long or short the respective indices that compose our investment universe. Last, **we updated the semi-sector neutrality defining maximum limits for the portfolio weights of +/-5%** for the difference between long and short leg for each industry.

From a macro standpoint, we come from six months of moderate stock indices growth, with the US performed better mainly due to the performance of large-cap technology firms. Interest rates seem to have reached the top with inflation in both the US and Europe coming down. Nevertheless, we expect inflation to be stickier than expected as the last "mile" to reach the 2% target often required higher for longer policies. In addition, the anticipated median inflation by the ECB for the next 12 months increased to 4%. Moreover, we expect constant or increased energy prices for the next 12 months that will make inflation stickier influenced by ongoing and new global tensions.

Based on our macroeconomic view, our factor allocation will be conservative for this semester. We will significantly increase the weight on quality from 20% to 35% while keeping value at 20%. We decreased the weight on size to 15% and inverted the factor. We also cut the weights on Momentum (now 10%) and ESG (now 5%) by halving them and reduced low volatility to now 15%.

Fund Factors

Value Factor – Long position

- Price-to-Book Value (P/(BV+OBS)): following the broad evidence provided by existing literature (e.g., Fama-French (1993)), we regard a high P/BV as a signal of relative overvaluation. We thus consider it as a selling indicator, since it shows that the company's equity is very expensive when compared to its underlying book value. This semester, we have added an estimate of off-balance-sheet (OBS) intangibles to the book values.
- EV/FCF: we regard a high EV/FCF as a selling signal, because it shows that the company is not able to generate a satisfactory level of FCF when compared to the value of the assets used to generate it. From last semester, we changed from EBITDA to FCF, as explained on page 6 of the report.

Momentum Factor – Long position

- MOM: following the evidence provided by Jegadeesh and Titman (1993) and Asness (1994), we consider momentum, defined as the sum of the 12 monthly returns preceding the last one divided by 11, as a buy signal. In practice, we assume that the stocks that had a recent high average return will keep doing well in the 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.
- Earnings Quality: for safety we also use the earnings quality to measure how reliable a company's reported net income is by comparing it to its cash from operations.

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.

Size Factor – Short position (inverted this semester)

- Free-Float Market Capitalization: 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).

ESG Factor – Long position

- Refinitiv ESG Score: we assume a higher ESG score to be a positive signal, since it reveals more attention to sustainability within a firm. Several papers show that, in the long run, a higher ESG score allows sustainable companies to perform equally or even better than traditional ones, showing an improvement in risk-adjusted returns.

Portfolio Composition

The rebalancing of the long-short portfolio consists in buying stocks with the highest total score and short-selling stocks with the lowest, while liquidating all our previous positions. Each of the six factors has an individual weight based on our macroeconomic view. In addition, this semester we introduce score-based weights for each selected stock. With this we overweight stocks where our conviction is even stronger and increase our exposure to the selected factors across the long and short leg of our portfolio.

The total score for each security is the sum of the final scores of the factors (after having applied triple Winsorization technique and the data normalization procedure) weighted by their factor specific weight.

Finally, consistently with the previous rebalancing of the portfolio, a «semi» sector neutrality has been implemented. Indeed, a cap of 20% (+2% vs. last semester) has been applied to all sectors as well a long/short difference cap of 5%. We do this to avoid excessive over- or under-exposure either in the short or in the long leg of our strategy without altering significantly the inherent philosophy of the model.

It is important to stress that the above-mentioned procedure did not involve stock-picking of any kind. In fact, companies were substituted only for the «semi» sector neutrality feature.

To maintain the β-neutrality (the beta for the current portfolio equals to -0.115), we included two future long positions: €15,475 on the S&P 500 and €7,581 on the STOXX EUROPE 600.

Factor weights

Value (20%)	Price/(Book Value + OBS)	10%
	EV/FCF	10%
Size (15%)	Free-Float Market Cap.	15%
Momentum (10%)	Asness (1994) Momentum	10%
Quality (35%)	Profitability: ROE	11.67%
	Growth: ROE 5y growth	11.67%
	Safety: D/E	5.83%
	Safety: Earnings Quality	5.83%
Low Volatility (15%)	Standard deviation	15%
ESG (5%)	Refinitiv ESG Score	5%

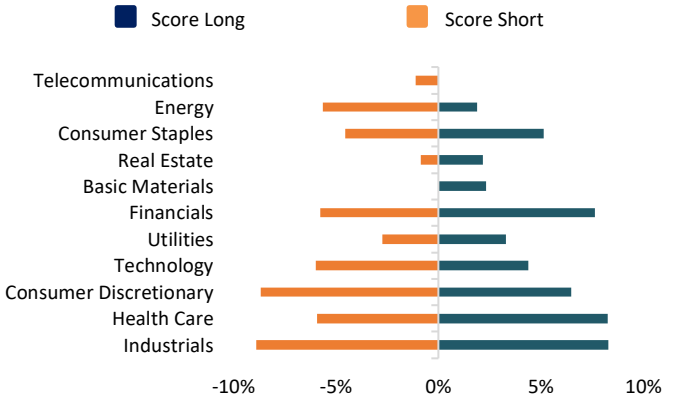
New Fund Positioning

S&P 500

CENCORA INC	1.023	PARAMOUNT GLOBAL	-0.630
BOEING CO	0.973	MONOLITHIC POWER	-0.752
AON PLC	0.949	MATCH GROUP	-0.778
HILTON HOLDINGS INC	0.812	SOLAREDGE TECH.	-0.779
AMGEN INC	0.811	MOHAWK INDUSTRIES	-0.789
VERTEX PHARMACEUTICALS	0.788	CATALENT INC	-0.827
SOUTHERN CO	0.773	ZEBRA TECHNOLOGIES	-0.828
MASTERCARD INC	0.769	KEYCORP	-0.847
VISA INC	0.731	BAXTER INTERNATIONAL	-0.858
PUBLIC STORAGE	0.728	VF CORP	-0.865
APPLE INC	0.714	GENERAC HOLDINGS INC	-0.904
PHILIP MORRIS	0.683	ZIONS BANCORPORATION	-0.911
AMERICAN INT.	0.675	BIO RAD LABORATORIES	-0.943
MCDONALD'S CORP	0.674	FIDELITY SERVICES	-0.949
COSTCO WHOLESALE	0.652	PAYCOM SOFTWARE	-1.135
COCA-COLA CO	0.646	AES CORP	-1.274
LINDE PLC	0.563	WALGREENS BOOTS	-1.290
BROADCOM INC	0.551	ENPHASE ENERGY	-1.445
WASTE MANAGEMENT	0.548	ETSY INC	-1.507
EQUINIX INC	0.542	NORWEGIAN CRUISE LINE	-1.533

STOXX EUROPE 600

NOVO NORDISK 'B'	0.975	LXI REIT	-0.675
INDITEX	0.805	FRONTLINE (OSL)	-0.836
KUEHNE UND NAGEL INT	0.780	SES FDR	-0.841
AIRBUS	0.772	WORLDLINE	-0.865
ROCHE HOLDING	0.755	GENUS	-0.866
L AIR LQE.SC.ANYME. POUR	0.740	MILLICOM INTL.CELU. SDR	-0.869
ROLLS-ROYCE HOLDINGS	0.725	ENCAVIS	-0.897
FERRARI (MIL)	0.681	DELIVERY HERO (XET)	-0.897
A P MOLLER MAERSK B	0.674	HELLOFRESH (XET)	-0.905
ALLIANZ (XET)	0.655	PHOENIX GROUP HDG.	-0.913
STELLANTIS	0.651	THYSSENKRUPP (XET)	-0.935
VINCI	0.643	ST.JAMES'S PLACE ORD	-0.947
NOVARTIS 'R'	0.638	TOMRA SYSTEMS	-0.951
QIAGEN (XET)	0.630	KINNEVIK B	-0.958
SAP (XET)	0.615	NORDIC SEMICONDUCTOR	-1.015
ASML HOLDING	0.597	ENERGEAN	-1.054
3I GROUP	0.590	INDIVIOR	-1.187
IBERDROLA	0.562	NEL	-1.190
HANNOVER RUECK (XET)	0.561	OCADO GROUP	-1.403
SHELL	0.546	WATCHES OF SWITZ GR	-1.434



Beta		Beta-neutrality countermeasures	
US-leg Beta	-0.155	S&P500	€15.475
European-leg Beta	-0.076	STOXX EUROPE 600	€7,581
Portfolio Beta	-0.115		

Performance

The last portfolio allocation took place on May 1, 2023. Therefore, our timeframe are the 7 months from May 1 2023 to November 30th 2023. Over this period, the portfolio obtained an absolute return of **€ 552.3** starting from **€ 100,000 of total exposure (1.0% 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 **€ 30,969.3.** However, **more than 60%** 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 this semester as well as 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 **€ 314.96**. Then, the **STOXX EUROPE 600 long-short leg** contributed with an almost equal amount of **€ 237.34**. It is fair to add that after three months of negative results, the fund showed strong performance in the following three months, then descending from the end of October until today. As a matter of fact, seven-months fixed investment with no rebalancing opportunity exposes us to market variations due to **high volatility** and changes in the **macro environment**.

By diving more deeply, we can see that the **best performers** in the S&P 500 leg of the portfolio were **DISH Network** (short, -50.7% over the period), followed by **Illumina Inc.** (short, -49.8%) and **Enphase Energy** (short, -37.7%). The worst performers were instead **NVIDIA Corp** (short, 70.6%), **TESLA Inc** (short, 47.8%) and **AMAZON.com Inc** (short, 40.2%). Both the best and worst performances were driven by short positions. In particular, the best performers scores were driven by an equal factor exposure, while the worst performing companies were mainly selected due to the size factor which led us to short large companies. Thus, the fund has been affected by the recent performance of big tech firms.

Looking at the **STOXX Europe 600 leg**, the **best performances** come from **Embracer Group** (short, -57.3% over the period), **Talanx** (long, +53.1%) and **Wise A** (short, -46.0%). The worst performers were instead **Vonovia** (short, +35.7%), **Salmar** (short, +31.5%) and **Fastigeths Balder B** (short, +28.7%). In Europe the size factor has been less impactful.

Overall, the fund has endured in a period of volatility and great uncertainty – especially in Europe. Despite the negative size effect, an appropriate combination of factors has been a convenient strategy in the past seven months. The cumulative performance of the fund highlights that the selection of factors to invest in shows reliable positive returns since the inception of the fund.

Previous Allocation Performance (May 1, 2023 – November 30, 2023)

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

Top Performer: Embracer Group (Short)

Embracer Group is a Swedish video game and media holding company headquartered in Karlstad, Sweden. The group suffered **severe losses** in May, when it announced an initial $2bn **investment partnership** with Amazon Games for the developing of a new **"The Lord of the Rings" video game**. The program was then **abandoned** a few days later.

Among the reasons why the model shorted Embracer Group there were: (i) **high volatility**; (ii) **high D/E** and **low ROE,** resulting in poor quality score; (iii) **negative momentum.**

Source: Refinitiv, Total Return Index

Worst Performer: Nvidia Corp (Short)

Nvidia Corporation is a **California-based** multinational technology company, leader in the **artificial intelligence hardware and software** sector. In 2023, it has exceeded expectations, driven by both the **"AI race"** and Nvidia's key role as a micro-chip supplier, amid **supply chain challenges** arising from tensions between the US and China.

The model shorted the stock given (i) its **extremely high EV/EBITDA** and general valuation**;** (ii) **high volatility.**

Source: Refinitiv, Total Return Index

Cumulative Performance (November 21, 2021 – November 30, 2023)

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

Redefining the Value Factor

QARP has been a consecutive factor selection for this fund (55% of our factor weights this semester). As we already examined and redefined the Quality factor last semester, we now take a deeper dive into the Value factor. This is also motivated by the fact that the value factor has been underperforming in the last years and does not seem to capture the risk premium as well any longer.

The proportion of off-balance-sheet (OBS) intangible capital to businesses' total assets has been increasing to around 50% in recent years, according to Ewens et al. (2023). This may help explain some of the underperformance of the value factor in the past decade, while the value factor including OBS intangibles has been steadily increasing (see Graph 1).

Attempting to capture some of these hidden values, we redefine the value factor to include OBS intangible assets. To do this, we use the results from the same paper (Ewens et al., 2023), and follow the approach of Gulen, et al. (2023) to define new parameters to be used for the scoring mechanism in the value factor.

This means adding OBS intangibles estimated through the approach in Ewens et al. (2023) to the Book-to-Market ratio and using FCF instead of EBITDA in the EV/EBITDA metric, as shown on page 2 of this report. FCF, representing cash available to investors, avoids mismeasurement issues common with earnings values.

The way OBS intangibles are estimated is through a non-linear regression (Equation (1)). The estimates are shown in Table 1. To simplify, we have for now opted to use the parameters under the "All" category.

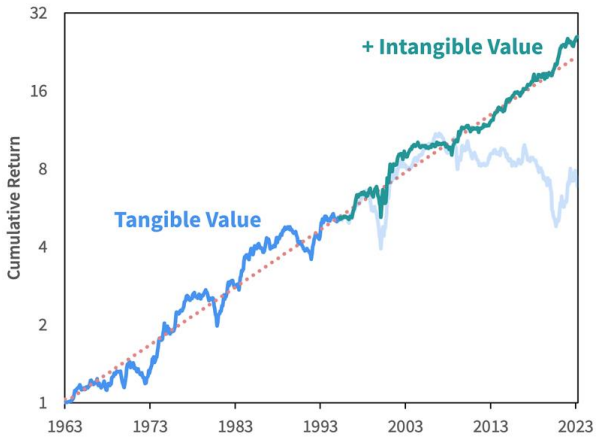
While book-to-market ratios have trended downward, free cash flow to price ratios have remained stable (see Graph 2), indicating that traditional GAAP measures fail to capture all productive capital (Gulen, et al. (2023), pp. 2). To illustrate this, it is shown that by adding OBS intangibles to the classic FF5F model, the maximum Sharpe-ratio offered roughly doubles, and the increase is statistically significant (see Table 2) (Gulen, et al. (2023), pp. 5, pp. 35).

$$\log(P^I_{it}) = \log(\rho_{jt}) + \log\left(\sum_{k=0}^{\infty}(1-\delta_G)^k \mathrm{R\&D}_{i,t-k} + \sum_{k=0}^{\infty}(1-0.2)^k \gamma_S \mathrm{SG\&A}_{i,t-k}\right) + \epsilon_{it}$$

Equation 1:
Source: Ewens et al. (2023).
P^I_{it} represents the price of the company's OBS intangible assets, and is estimated through the R&D and SG&A expenses. SG&A expenses are assumed discounted at 20%, thus the proportion of its expenses actually invested into OBS capital is estimated. On the other hand, all of R&D is assumed to be invested into OBS capital, thus its depreciation rate is estimated. Log(ρ_{jt}) is assumed to be equal to zero in the paper. The results are stated in Table 1.

	BEA-HH		
	(1)	(2)	(3)
	γ_S	δ_G	$\neq .15$
All	0.30	0.23	52%

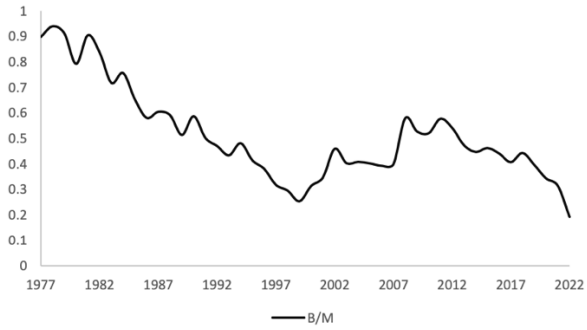
Table 1:
Source: Ewens et al. (2023).
γ_S represents the estimate for the proportion of SG&A expenses invested in intangibles, for all industries. δ_G represents the annual discounting for R&D expenses, also across all industries.



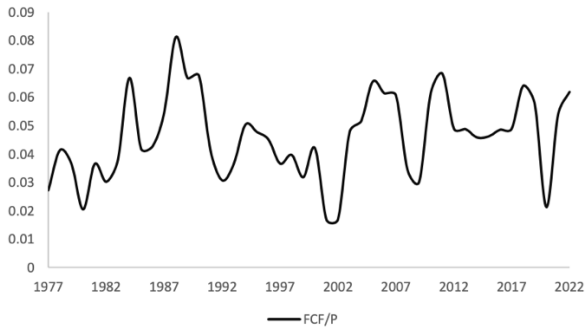
Graph 1:
Source: Wu (2022) and Wu (2021), Sparkline Capital.
The graph shows how the standard HML value factor (blue) and HML including OBS intangibles (green) performed over the past years

Model A			Model B			SR Test
Factor	Weights	SR	Factor	Weights	SR	(A-B)
Panel A. Proposed model versus Fama-French five-factor model						
MKT	0.14	0.40	MKT	0.25	0.27	2.24
SMB^{PPE}	0.05		SMB^{PPE}	0.33		
HML	-0.20		HML	-0.12		
HML^{OBS}	0.46		CMA^{PPE}	-0.18		
CMA^{PPE}	-0.30		RMW	0.72		
CMA^{OBS}	0.32					
RMW^{total}	0.52					

Table 2:
Source: Gulen et al. (2023).
Model B is a conventional Fama-French 5 factor model, with a Sharpe-ratio of 0.27. On the other hand, adding factors with OBS values (Model A), the Sharpe-ratio increases to 0.40 (highlighted).



(A) Book-to-Market



(B) Free Cash Flow to Price

Graph 2:
Source: Gulen, et al (2023).
The BV/P metric has been trending downwards over time, while the FCF/P metric has been evolving steadily around its mean. This motivates our change to FCF in our EV/FCF metric (previously EV/EBITDA).

Taking care of ESG

The ESG factor can be difficult to quantify, both as ESG ratings differ between rating agencies, and because, as (Lioui, Tarelli, 2022) demonstrates, the estimation technique for the factor itself can vary in the literature. This, together with the conflicting literature, led us to consider removing the ESG factor from our fund but in a meta-study by Kumar (2022), it was found to have an effect on portfolio alpha for regionally diversified portfolios with a heavy weighting towards the developed market portfolio. There is according to Kumar (2022) no link between ESG and alpha in other portfolios.

Taking these uncertainties into account, but also considering the possibility of having a link to alpha in our portfolio, we have decided to maintain the ESG factor, but lower the weight relative to the other factors. Therefore, from this semester onwards the ESG factor weight will remain at 5%.

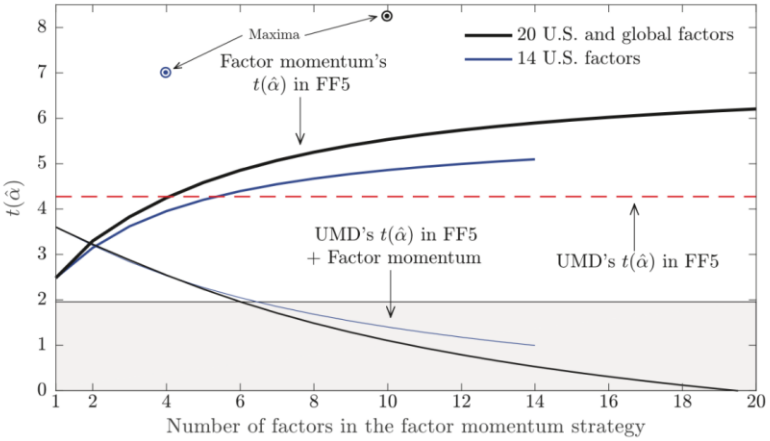
Riding the wave of momentum

The downscaling of the momentum factor in our factor allocation is primarily based on the finding that momentum in individual stock returns is closely related to momentum in factor returns.

Ehsani and Linnainmaa (2022) demonstrate that most factors are positively autocorrelated, and this autocorrelation is particularly strong in high-eigenvalue principal component factors, which encompass most forms of individual stock momentum.

This highlights that momentum may essentially be about timing other factors, rather than being an unrelated, distinct risk factor. The loadings of momentum stocks on these factors change over time, leading to the impression that momentum is distinct from other risk factors. However, Ehsani and Linnainmaa (2022) argue that all of momentum profits can be captured by timing other factors, suggesting that there is no need to construct a separate momentum factor from security-level data. Despite this, investors cannot entirely ignore momentum; they still need to time other factors or redefine existing factors to capture momentum effectively.

We view momentum as a highly relevant factor we would like to focus on. However, seeing it can be captured in large part by trading the momentum of the other factors, we have decided to downscale our weighting. We do not remove it completely as we do not wish to rely solely on timing of other factors, nor do we wish to redefine our factors to entirely encapsulate the momentum factor.

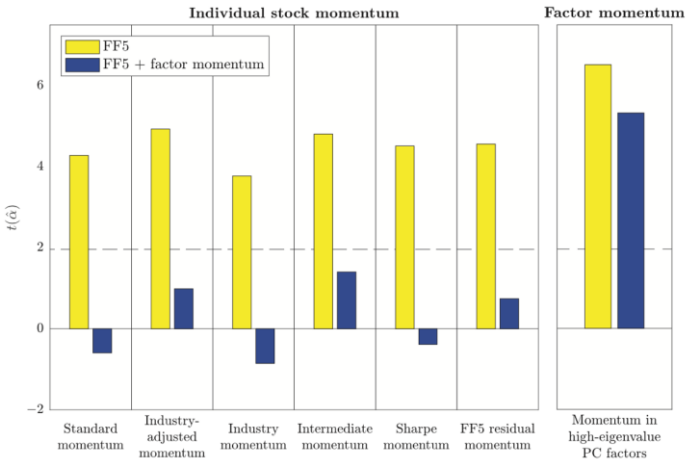


Graph 3:
Source: Ehsani and Linnainmaa (2022).

The researchers construct long/short portfolios, going long factors with positive momentum, and short factors with negative momentum. These are called factor momentum strategies, as they are a bet on the momentum within the factors themselves. The number of factors added to the strategies is measured on the x-axis, while the t-stats of the different strategies is measured on the y-axis.

The thick lines represent the factor momentum strategy's average *t*(α)s from the Fama-French five-factor model regression with 20 (black) and 14 (blue) factors, and the thin lines represent UMD's average *t*(α)s from a regression that augments the five-factor model with the factor momentum strategy. The dashed line denotes UMD's *t*(α) from the Fama-French five-factor model regression, while the circles denote the combinations with the highest *t*-values in the two universes of factors. The shaded region indicates *t*-values below 1.96.

UMD is the classic momentum factor (Up-Minus-Down).



Graph 4:
Source: Ehsani and Linnainmaa (2022).

Each momentum strategy is ordered along the x-axis, with 2 bars each; standard Fama-French 5 factor model (yellow), and an augmented FF5fm to capture factor momentum (blue). The first 6 strategies trade individual stocks, while the 7th (right-most) strategy trades the first 10 Principal Component portfolios constructed from 47 factors.

For the first 6 strategies, t-stats of the alphas of the different strategies is measured on the y-axis. We see that including factor momentum renders the alphas insignificant (blue bars under the 1.96 dashed line).
In the 7th barplot, the t-stat for the factor momentum alpha itself is measured, and we see that it is always statistically significant.

Quantitative Research Team

Risk Report – December 2023

Introduction

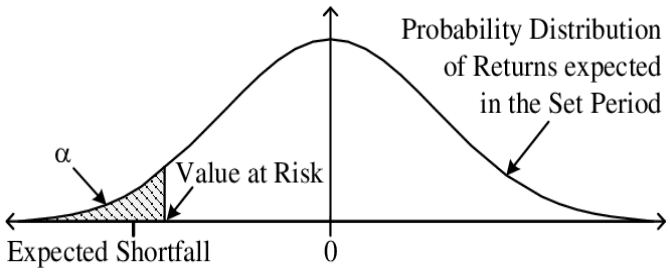
The main objective of this section is to assess and quantify the risk embedded in the Minerva IMS Long-Short Equity Fund built by the portfolio team. We use a daily perspective on the potential extreme behavior of a basket of assets selected by the portfolio analysts. The analysis will include three 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 Investment Risk 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 α% of probability over a time horizon of 1 day. For instance, if the VaR (α=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 α% 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.



Head of Quantitative Research
Umberto Barbieri: barbieri.umberto@studbocconi.it

Analysts

Erik Bergqvist: kjell.bergqvist@master.unibocconi.it
Francesco Braicovich: francesco.braicovich@studbocconi.it
Giacomo Gregori: giacomo.gregori@studbocconi.it
Antonio Petrai: antonio.petrai@studbocconi.it
Enrico Sammarco: enrico.sammarco@studbocconi.it
Vasileois Stavropoulos: vasileios.stavropoulos@studbocconi.it
Nathan Van Es: nathan.vanes@studbocconi.it
Erik Vik: erik.vik@studbocconi.it

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 it's 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 Fn, is:

$$Dn=\sup x|(Fn-F)|$$

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:

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

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.

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:

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

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:

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

where $\boldsymbol{VaR_\alpha}$ and $\boldsymbol{ES_\alpha}$ are column vectors of individual stock VaR and ES, respectively and $\boldsymbol{\rho}$ 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
$VaR_{95\%}$	-3.12%	-3.28%
$VaR_{99\%}$	-4.50%	-4.61%
$ES_{95\%}$	-3.86%	-3.95%
$ES_{99\%}$	-4.73%	-4.91%

TOP & BOTTOM 5 stocks (simple approach)

	VaR 95	VaR 99	ES 95	ES 99
ALLIANZ	-1.52%	-2.21%	-1.95%	-2.57%
MCDONALDS	-1.54%	-2.21%	-1.95%	-2.56%
COCA COLA	-1.58%	-2.24%	-1.99%	-2.58%
IBERDROLA	-1.57%	-2.27%	-2.00%	-2.64%
VISA 'A'	-1.62%	-2.33%	-2.06%	-2.70%

	VaR 95	VaR 99	ES 95	ES 99
ENPHASE ENERGY	-6.66%	-9.55%	-8.44%	-11.14%
SOLAREDGE TECHNOLOGIES	-6.77%	-9.54%	-8.47%	-11.00%
ZIONS BANCORP.	-6.67%	-9.67%	-8.52%	-11.29%
WORLDLINE	-7.57%	-10.71%	-9.50%	-12.33%
OCADO GROUP	-8.17%	-11.70%	-10.34%	-13.52%

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
$VaR_{95\%}$	-3.09%	0.30%
$VaR_{99\%}$	-4.54%	0.44%
$ES_{95\%}$	-3.90%	0.30%
$ES_{99\%}$	-4.83%	0.35%

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 $M \to +\infty$ (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)
VISA 'A'	-1.62%	-2.37%	-2.08%	-2.76%
VINCI	-1.57%	-2.53%	-2.18%	-3.18%
IBERDROLA	-1.75%	-2.86%	-2.46%	-3.70%
MCDONALDS	-1.94%	-2.79%	-2.46%	-3.23%
MASTERCARD	-1.94%	-3.14%	-2.70%	-4.00%

	VaR 95 (GARCH)	VaR 99 (GARCH)	ES 95 (GARCH)	ES 99 (GARCH)
ZIONS BANCORP.	-10.07%	-18.03%	-15.38%	-25.52%
V F	-11.09%	-19.71%	-16.86%	-27.94%
OCADO GROUP	-11.04%	-20.98%	-17.94%	-32.07%
ROLLS-ROYCE HOLDINGS	-10.47%	-22.98%	-19.83%	-41.10%
CATALENT	-13.97%	-30.74%	-26.63%	-55.69%