

MIMS – Long-Short Equity Fund

Portfolio Management Team

Report – May 2024

Fund Description

MIMS – Long Short Equity Fund is a semi-automated activelymanaged 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

- 2024 is a year dominated by elections, with over 60 countries, including the US, holding presidential, congressional, and local elections. This may bring market volatility. The US started the year with a 5.5% interest rate and planned cuts, but persistent inflation causes some doubts. However, the Fed Chair Jerome Powell stated that a hike move in the interest policy will be unlikely.
- Initial hopes of lowering inflation rates to 2% in the US are fading. CPI data shows it remains strong at 3.4% year-over-year (YoY) with a 0.3% increase from March to April. Therefore, investors seek higher yields, pushing them towards US corporate bonds and European bonds, where the ECB is expected to reduce the inflation rate to 2.4% in 2024 and 2% in 2025. However, a significant US rate hike could weaken the Euro, causing imported inflation in the EU.
- High interest rates, stubborn inflation, and investor uncertainty have yielded negative returns for the S&P 500 and STOXX Europe 600 in the first two weeks of April. Notably, the "Big Six" tech stocks (Amazon, Apple, Alphabet, Nvidia, Meta, Microsoft) have seen a significant downturn. Tesla also suffered from falling delivery estimates, experiencing a -40% YTD return. Interestingly, J.P. Morgan data shows S&P 500 returns average 6.2% in election years compared to 9.6% in non-election years, with slightly higher volatility.
- While concerns exist about the US Shale Revolution ending, natural gas and crude oil production are rising. The EIA forecasts US oil production to average 13.2 million barrels per day (mbpd) in 2024 and 13.4 mbpd in 2025, exceeding the 2023 record of 12.9 mbpd. Despite recent conflicts, oil prices remain stable at around \$87 per barrel, demonstrating the Shale Revolution's impact on the global oil map and geopolitical balance.



Head of Asset Management Giuseppe Palermo: giuseppe.palermo@studbocconi.it

Head of Portfolio Management Anna Maruccio: anna.maruccio@studbocconi.it

Portfolio Manager

Erik Vik: erik.vik@studbocconi.it

Portfolio Analysts

Michele Rinaldi: michele.rinaldi@studbocconi.it Aleksandar Georgiev: aleksandar.georgiev@studbocconi.it Giovanni Carboniero: giovanni.carboniero@studbocconi.it Francesco Anastasi: arancesco.anastasi@studbocconi.it Vasileios Stavropoulos: vasileios.Stavropoulos@studbocconi.it Antonio Petrai: antonio.petrai@studbocconi.it

Factor Investing Strategy					
VALUE	MOMENTUM				
QUALITY	LOW VOLATILITY				
SI	ZE				

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 initiated a period of major transition. Previously, all calculations and decisions have been made on a fundamental basis, meaning that all scores have been computed from the last few years' average of a fundamental score. This could for example be the last 4 years average ROE score. To start orienting the fund towards a time-series based approach, the fund is now based on Python instead of Excel, and will allocate capital toward or away from companies exposed to the factors' time series' returns. The model will be improved over time.

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 can be constructed by ranking assets according to some metric (e.g. book-to-market ratio) assumed to capture said factor. For example, one can rank assets according to the market capitalization if looking for size. Then, the assets are formed into portfolios, usually 5 or 10. In this fund, decile portfolios are used. Each time period (here monthly), the assets are re-ranked into these portfolios.

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.

Following a style-analysis approach, we regress each stock in our investable universe on our 5 factors and extract the coefficients to the factors. They are then standardized and winsorized (if needed) to get z-scores for each factor. These are treated as a given company's exposure to the factor. When the exposures are collected, we calculate a weighted average final score for each company based on our discretionary weighting (found under "Factor Weights") and rank them.

Thereafter, qualitative checks are done to ensure sector neutrality. The remaining 20 stocks in each leg (short/long, EU/US) will be the final constituents of the portfolio, and their weights are standardized to sum to 1 for the long leg, and 1 for the short leg. The final sum of weights is zero. In this way, we take a stronger position on companies for which we have a stronger score based on the model.

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. In practice, we assume that the stocks that had a positive average return in the last months will keep doing 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 5year 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.
- 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 towards the SMB factor in Kenneth French's data library.

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Tactical Decisions

This semester we reduced the short on the SML (size) factor to 10%. This is because we still believe in the higher for longer interest rate environment which was the argument behind last semester's short. However, the evidence is not as strong, thus reducing our short closer to zero. We still want to capture underpriced companies, so the HML (value) factor was allocated 20%, no change from last semester. Drawing from academic research (see page 7), we decided to set the weight for the ESG factor to zero, removing it completely from this semester's portfolio.

We still believe in the continued relevance of the momentum anomaly, giving it a 20% weight, an increase from 10%. The Low Idiosyncratic Volatility anomaly has been allocated 30%. The large weight in the latter comes partly from a risk-budgeting approach. As the Low IVOL long-short "factor portfolio" is a portfolio with low variations in its returns, the overall contribution to the risk of our portfolio will be miniscule. A famous example of this is the classic 60/40 portfolio with equities and fixed income, where equities account for over 90% of the overall risk. Low volatility is also used as a defensive strategy against potentially volatile markets in the upcoming election season in the US and EU.

The quality factor continues to be an important part of our portfolio with 20% allocation. This is also based on our belief that if we see a higher interest level going forward, companies with high earnings quality will perform relatively better than those without.

All weights are done with a score-based method, where the final weighted factor scores are normalized to sum to one for each region. To keep our portfolio neutral towards industry movements, some companies are replaced from the industries we are overweight in and replaced with high (low) scoring companies for the long (short) leg from an underrepresented sector (see bar chart). It is important to stress that the abovementioned procedure did not involve stock-picking of any kind. In fact, companies were substituted only for the «semi» sector neutrality feature.

Factor weights				
Value (20%)	High-Minus-Low Book-to-Market (HML) Factor	20%		
Inverted Size (10%)	Small-Minus-Big Market Capitalization	10%		
Momentum (20%)	Carhart (1997) Momentum	20%		
	Profitability: ROE	3,75%		
Quality (20%)	Growth: ROE 5y growth	7,5%		
	Debt to Equity	3,75%		
	Earnings Quality	5%		
Low Volatility (30%)	Standard deviation of idiosyncratic errors from factor model	30%		

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New Fund Positioning

S&P 500

VERALTO CORP	2,762	AIRBNB INC	-1,90
KENVUE INC	1,362	DAYFORCE INC	-1,44
PG&E CORP	0,982	ETSY INC	-1,400
EQT CORP	0,916	CATALENT INC	-1,259
CF INDUSTRIES HOLDINGS INC	0,861	CAESARS ENTERTAINMENT INC	-1,23
INSULET CORP	0,777	UBER	-1,052
NEWMONT CORPORATION	0,731	GE HEALTHCARE TECHNOLOGIE	-0,97
NORTHROP GRUMMAN CORP	0,568	ARISTA NETWORKS INC	-0,973
UNITED AIRLINES HOLDINGS INC	0,531	DUPONT DE NEMOURS INC	-0,962
WALGREENS BOOTS ALLIANCE INC	0,524	CONSTELLATION ENERGY CORP	-0,959
DELTA AIR LINES INC	0,509	FORTIVE CORP	-0,903
GILEAD SCIENCES INC	0,509	INVITATION HOMES INC	-0,870
DOLLAR GENERAL CORP	0,509	MATCH GROUP INC	-0,874
CAMPBELL SOUP CO	0,496	INGERSOLL RAND INC	-0,869
AKAMAI TECHNOLOGIES INC	0,482	APTIV PLC	-0,843
SOUTHWEST AIRLINES CO	0,475	DOW INC	-0,75
ABBVIE INC	0,452	IQVIA HOLDINGS INC	-0,750
BOEING CO	0,450	SYNCHRONY FINANCIAL	-0,740
CONAGRA BRANDS INC	0,446	ALIGN TECHNOLOGY INC	-0,689
MERCK & CO INC	0.441	ZOETIS INC	-0.688

STOXX EUROPE 600

AIB GROUP		1,267	EQT			-1,982
AIXTRON (XET)	IXTRON (XET)		WISE A			-1,794
OCI		1,128	KION GROU	P ()	(ET)	-1,578
BPER BANCA		1,118	VAT GROUP	•		-1,396
GLENCORE		1,014	ALLFUNDS O	GRO	UP	-1,330
ANGLO AMERICAN		0,999	ZALANDO ()	KET)	-1,319
BANKINTER 'R'		0,997	LIFCO B			-1,218
UBISOFT ENTERTAI	NMENT CAT A	0,975	DR ING HC	F PC	DRSCHE(XET) PRE	-1,178
LEONARDO		0,928	HELLOFRES	H ()	(ET)	-1,119
DIRECT LINE IN.GR	OUP	0,922	SIEMENS ENERGY N (XET)		-0,506	
STANDARD CHARTERED		0,904	IMCD GROUP		-1,044	
PEARSON		0,898	AMUNDI (WI)		-0,890	
BT GROUP		0,569	SPIE		-0,888	
FORTUM		0,841	NORDNET		-0,811	
OCADO GROUP		0,835	SIEMENS (XET) HEALTHINEERS		-0,879	
LPP		0,823	ALCON (SWX) ORD SHS		-0,856	
BP		0,807	VALMET		-0,843	
GENMAB		0,782	EPIROC A		-0,842	
INMOBILIARIA COLONIAL		0,520	SIG GROUP	Ν		-0,818
GRIFOLS ORD CL A		0,731	OERSTED			-0,778
	Score Long	5			Score Short	



Neutrality Hedges

Given the companies in our proposed portfolio allocation, the beta over the last year seems to be in line with last semester's.

For the European leg of the portfolio, the 19 month historical beta using daily observations has been -0.2503. For the US leg, the raw 7-month beta has been -0.3204. The reason for the much smaller sample period in the US leg is mostly due to stocks like Veralto and Kenvue, which started trading on the NYSE on the 2nd of October 2023 and 4th of May 2023 respectively.

These betas reflect a slightly inverse sensitivity to their underlying indices, STOXX EURO 600 and S&P 500, signifying the importance of beta hedging if one wishes to stay neutral to the underlying movements in the indices. This is how one can extract the premia from the factors and anomalies we allocate to. Both hedges land on less than one contract, but we shall round up.

A caveat here is that the beta exposures will change over time, meaning that the portfolio beta could be very different in a few weeks or months time. The only way we can stay beta-neutral at all times is to dynamically hedge with the futures on the underlying indices. This is not done in this fund, as allocations are rebalanced every semester.

Another risk the fund faces is currency risk. Being a zero initial investment fund, our currency risk at inception is zero. However, much like the beta exposure, this is subject to change as the payout in USD will not correlate perfectly the payout in EUR. However, no currency hedge has been implemented as of now.

Beta-neutrality countermeasures (number of LONG contracts) Prices taken on 01.05.2024

Micro E-mini S&P	$0.22^{\text{€50'000} \times 1.08(\text{$/€)}} \approx 1 \text{ cont}$
500 (Dec. 2024)	$-0.32 - 5052.50 * 5 \approx 1.00 \text{ m}$
STOXX EUROPE 600	€50′000
(FXXP, Dec. 2024)	$-0.25 \frac{-0.25}{512.50 \times 50} \approx 1 \text{ contract}$



		OLS	S Regressior	ı Resul	ts			
Dep	. Variable:		US PTF		R-squa	ared:		0.297
	Model:		OLS	A	dj. R-squa	ared:		0.292
	Method:	Le	ast Squares		F-stat	stic:		59.22
	Date:	Mon, 2	0 May 2024	Prol	b (F-statis	stic):	2.3	0e-12
	Time:		01:03:32	L	og-Likelih	ood:	5	95.94
No. Obs	ervations:		142			AIC:		-1188.
Df I	Residuals:		140			BIC:		-1182.
	Df Model:		1					
Covaria	nce Type:		nonrobust					
	coef	std err	t	P> t	[0.025	0.97	′5]	
const	0.0002	0.000	0.483	0.630	-0.000	0.0	01	
SP500	-0.3204	0.042	-7.695	0.000	-0.403	-0.2	38	
O	mnibus:	2.729	Durbin-W	atson:	1.865			
Prob(On	nnibus):	0.256	Jarque-Bera	(JB):	2.299			
	Skew:	0.299	Pro	o(JB):	0.317			
к	urtosis:	3.179	Con	d. No.	135.			

	OLS	S Regressi	on Result	s		
Dep. Variable:		EU P	TF	R-squ	ared:	0.124
Model		0	LS Ad	j. R-squ	ared:	0.121
Method	: Le	ast Squar	es	F-stat	istic:	55.95
Date	: Mon, 2	0 May 20	24 Prob	(F-stati	stic):	4.82e-13
Time		01:03:	31 Lo	g-Likelih	lood:	1546.0
No. Observations		39	99		AIC:	-3088.
Df Residuals:		3	97		BIC:	-3080.
Df Model			1			
Covariance Type:		nonrobu	ıst			
	coef	std err	t	P> t	[0.02	5 0.975
const 7.	838e-05	0.000	0.310	0.757	-0.00	0 0.00
EUROSTOXX	-0.2503	0.033	-7.480	0.000	-0.31	6 -0.184
Omnibus:	40.322	Durbin	-Watson:	1.7	737	
Prob(Omnibus):	0.000	Jarque-E	Bera (JB):	79.6	52	
Skew:	-0.578	1	Prob(JB):	5.06e	-18	
Kurtosis:	4.859	c	Cond. No.	1	33.	



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Performance

The last portfolio allocation took place on December 1, 2023. Therefore, our timeframe is the five months from December 1 2023 to April 30th 2024. Over this period, the portfolio obtained an absolute return of \notin 8272.26 starting from \notin 100,000 of total exposure (21.02% 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 \notin **39,241.60**. 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 **STOXX EUROPE 600 long-short leg**, which produced gains of \notin **5625.27** before beta-hedge. To compare, the **S&P 500 long-short leg** contributed with lower amount of \notin **532.32** before beta-hedge. The latter part of December presented a significant challenge with the portfolio experiencing negative returns. However, we are pleased to report a course correction in January, where an ongoing positive performance trend occurred. It is important to keep in mind the uncertain economic conditions as well as the initial drop in the market for AI technologies. By diving more deeply, we can see that the **best performers** in the S&P 500 leg of the portfolio were **Broadcom Inc.** (long, +40.81% over the period), followed by **VF Corp.** (short, -31.12%) and **Etsy Inc.** (short, -16.30%). The worst performers were instead **Boeing Co.** (long, -28.23%), **Catalent Inc.**(short, +39.10%) and **Zebra Technologies**(short, +30.4%). Both the best and worst performances were mainly represented by short positions. In particular, both the top and the bottom performers' scores were driven by an equal factor exposure (except for Zebra Technologies where Volatility accounts for 50% of the score).

Looking at the **STOXX Europe 600 leg**, the **best performances** come from **Watches of Switz. Gr.**(short, -45.02% over the period), **Rolls-Royce Holdings** (long, +49.80%) and **Ocado Group** (short, -36.62%). The worst performers were instead **Tomra Systems** (short, +35.64%), **Kinnevik** (short, +23.60%) and **Millicom Intl.** (short, +23.73%). No one of these value was predominantly calculated by one factor alone.

Overall, the fund has performed well in a period of moderate growth with interest rates kept high. The negative size factor introduced last semester, beyond eliminating the predominance of big firms in the short leg, has achieved the hoped results: factor exposure for our stocks is balanced and stable.

As shown by the cumulative performance of the fund, a set of balanced investment factors has consistently yielded positive returns since the fund's inception.

The (long) beta hedges added a total return of **€2114.67** as both markets increased in the period.



Previous Allocation Performance (December 4, 2023 – April 30, 2024)

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

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The Watches of Switzerland Group PLC is a British multinational luxury watch retailer headquartered in Braunstone, England. The company has sunk over **30% since December**, as revenue of £1.543 billion falls short of projections (£1.65-1.70 billion). Analysts cite a **challenging economic climate**, alongside Rolex's acquisition of Bucherer.

Among the reasons why the model shorted **The Watches of Switzerland Group PLC** there were: (i) **high volatility**; (ii) **negative earnings growth** and **negative earnings quality**, resulting in poor quality score.

Cumulative Performance (November 21, 2021 – April 30, 2024)



Boeing is a leading American multinational in the aerospace industry, headquartered that has recently faced significant challenges. The company's stock has plunged over 25% since December, largely due to a series of safety issues and quality control problems. These issues include multiple accidents involving blown door plugs, engine failures, and lost wheels, raising serious concerns and eroding investors' confidence.

The model takes long position in the stock, given (i) its **high EV/EBITDA** and (ii) **high P/BV**, resulting in a significant value factor positive score.

Source: Refinitiv, Total Return Index



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Source: Refinitiv, Total Return Index

	(1)	(2)	(3)	(4)
	CARBON_equal	CARBON_value	ESG_equal	ESG_value
МКТ	0.2757***	0.2427***	0.0404	0.0699
	(0.001)	(0.001)	(0.222)	(0.142)
SMB	-0.4132***	-0.2292**	-0.1338***	-0.1542**
	(0.000)	(0.014)	(0.004)	(0.020)
HML	0.0801	0.2243*	-0.0340	-0.0264
	(0.549)	(0.059)	(0.513)	(0.723)
RMW	-0.4683***	-0.3992***	0.0603	0.2516**
	(0.004)	(0.006)	(0.391)	(0.014)
CMA	0.0051	-0.4598**	-0.0643	-0.1934
	(0.981)	(0.015)	(0.461)	(0.124)
МОМ	0.1037	-0.0000	0.0347	0.0267
	(0.218)	(1.000)	(0.188)	(0.480)
BAB	0.0282	0.1978*	-0.1117***	-0.1920***
	(0.829)	(0.088)	(0.006)	(0.001)
QMJ_GROWTH	0.1721	0.2183	-0.0500	-0.2502**
	(0.460)	(0.288)	(0.475)	(0.014)
QMJ_SAFETY	0.8282***	0.3858**	0.2290***	0.3755***
	(0.000)	(0.021)	(0.001)	(0.000)
CONSTANT	0.0011	0.0004	-0.0002	-0.0010
	(0.656)	(0.837)	(0.872)	(0.500)
N	118	118	146	146
Adj R ²	0.4207	0.2936	0.3410	0.3800

FIGURE 1: The relationship between risk factors and CARBON and ESG factors

Source: Covachev, Martel and Brito-Ramos (2024)

The table shows the equation (1) parameter estimates.

The equal-weighted and value-weighted versions of the CARBON and ESG factors are both used. The equal-weighting scheme ensures meaningful representation of stocks with very low market capitalization values in the factor portfolios, whereas value weighting ensures representation that is proportional to the significance of each stock in the whole economy.

P-values are presented in parentheses. Coefficients with "*", "**", and "***" are significant at the 10%, 5%,and 1% levels, respectively.

Sample period: June 2009 to March 2019 for models (1) and (2) and February 2007 to March 2019 for models (3) and (4).



FIGURE 2: Slope coefficients of risk factors for the value-weighted ESG factor Source: Covachev, Martel and Brito-Ramos (2024)

The coefficients are estimated over a 5-year rolling window.

Only coefficients that exceed 0.20 in magnitude at least once during the estimation period are plotted

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Eliminating the ESG factor

As the world evolved, businesses followed the path to keep pace with the innovations. In recent decades, the concern for the environment has undergone radical changes: today, the ESG is no longer just a prophecy but a growing reality in the business world. But is the ESG factor useful and relevant for our purposes?

Precisely because of its recent use, we will rely on newly released studies. Bolton and Kacperczyk (2021) demonstrates that the green premium might be explained by the link between firms' carbon intensity and higher financial returns, suggesting a 'carbon premium' that cannot be adequately taken into account by ESG factors. Covachev, Martel and Brito-Ramos (2024) constructed a Carbon factor on negated carbon intensity and examined the relationships between the CARBON and ESG factors and the remaining factors in a standard OLS time-series regression¹.

Both ESG scores and carbon intensity are positively associated with profitability.

The quality factor growth part (ROE and 5ygrowthinROE) is negatively related only to the value-weighted ESG factor. In contrast, there is a strong positive relation between the safety component of the quality factor(D/Equity and Earning quality) and both the CARBON and the ESG factors.

Thus, financially safe companies are more likely to manage environmental risks well or be less exposed to them and adopt good ESG risk management practices.

Looking at the adjusted R^2 , more than 30% of ESG - or carbon intensity - are explained by the other Fama-French factors with which they should have little - if any - causal relations (see figure 1).

As we can see from figure 2, the slope coefficients of common risk factors vary considerably overtime for the value-weighted ESG factor. The carbon factor slope coefficients vary significantly too. Although it is not possible to rely on a single factor to replace esg, it is noteworthy that virtually all factors have a correlation and causal link with ESG.

The carbon and ESG risk factors can be

replicated as linear combinations of risk factors that are based on stock characteristics that are not directly related to environmental and ESG policies.

Moreover, Liang et al. (2024) discovered that ESG scores have a positive effect on mispricing: the implications are that certain ESG attributes might be relevant, but they are not efficiently incorporated into stock value.

1. OLS time-series regression $Y_t = \alpha + \sum_{k=1}^{K} \beta_k X_{k,t} + \varepsilon_t$

Source: Covachev, Martel and Brito-Ramos (2024).

- Y_t = CARBON_t or ESG_t is the value of the respective factor in month t.
- α is a constant.
- B_k is the slope coefficient of the k_{th} factor,
- $X_{k,t}$ is the value of the kth factor in month t e, is the value of the idiosyncratic error term in month t.
- The following 9 explanatory factors are used (K=9): MKT, SMB, HML, RMW, CMA, MOM, BAB, QUALITY GROWTH and QUALITY SAFETY.



Momentum Until Today

Momentum is a highly relevant factor each portfolio manager should take into account. However, it is noteworthy that it can be caught in part by trading the momentum of the other factors. It is crucial to highlight that even if Momentum can be captured through complex mixes of other - classic and more complex - factors, we have decided not to modify the model. This means that the classic Cahart momentum is still used.

Momentum is the factor where macroeconomic outlook can help the least, thus we need empirical data to understand how much importance it can have nowadays.

Gary Antonacci (2014) shows us that Momentum performed well during periods of decline: when the economy appears to be suffering, Momentum seems to rejoice in it. Generally, the momentum factor has achieved its best results during periods of moderate decline. Although it is not a defensive factor, darker periods - such as recessions - have not dented its performance as can be seen in Figure 3 and Figure 4.

However, historical data are not enough for our purpose; we need the most recent possible data in order to be conscious of the relevance of momentum in 2024.

The iShares MSCI USA Momentum Factor ETF (MTUM) has surged impressively by 18.6% from the beginning of the year until 10th April. Momentum has significantly outpaced the broader market's 9.6% increase (the red line in figure 5).

In addition to going twice as fast as the market, momentum was in the first part of 2024 the best factor among the Fama-French classic ones - and beyond.

Considering the current market situation and the recent MTUM performance, we decided to increase the weight of Momentum in our portfolio.

Date	MSCI US	60/40 Portfolio	Parity w/Abs Mom
3/74 9/74	-33.3	-22.4	+2.2
9/8711/87	-29.4	-17.0	-1.7
9/00 9/01	-30.9	-15.4	+5.4
4/02 9/02	-29.1	-12.2	+7.3
11/07 2/09	-50.6	-29.3	-0.4

FIGURE 3: Maximum Stock Market Drawdown 1974-2012 Source: Gary Antonacci (2014)

The table depicts the performances of three different funds during the worst crisis from 1974 to 2012:

- MSCI US = Index designed to measure the performance of the large and mid-cap segments of the US market.
 Cov(20) Participation of the large design of the large d
- 60/40 Portfolio = balanced stock/bond portfolio constructed with 60% equities and 40% bonds.
 Par w/Abs Mom: 60/40 portfolio plus REITs, credit bonds, and gold, with an equal
- weighting given to each asset class. During the creation of the portfolio, securities with higher Momentum were picked.

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Parity w/Abs Mom 60-40 Portfolio MSCLUS 0 -10 -20 -30 -40 -50 -60 2 2 2 2 2 200 9 0 0 ō

FIGURE 4: 5-Year Maximum Drawdown 1974-2007

Source:Gary Antonacci (2014) The table depicts the performances of three different funds from 1974 to 2012.

The "5-Year Maximum Drawdown" refers to the largest percentage decline in value experienced by an investment or portfolio over any five-year period. It measures the peak-to-trough decline during that time frame. In other words, it indicates the maximum loss an investor would have endured if they invested at the highest point and sold at the lowest point within any continuous five-year period

The portfolios and their structure are the same described in Figure 3.



FIGURE 5: Factor performances in the US in 2024 from January to mid-April

Source: The Capital Spectator (April 2024)

The names of the factors are illustrated on the x-axis. The performance of each

is measured by a specific ETF.

MTUM = iShares MSCI USA Momentum Factor ETF.

The red line is the SPY(SPDR S&P 500 ETF) representing the US market.

Data refers to the period January 1, 2024 - April 9, 2024.







Quantitative Research Team

Risk Report – May 2024

Introduction

The main objective of this section is to assess and quantify the risk embedded in the allocation 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

Giovanni Carboniero: giovanni.carboniero@studbocconi.it Michele Fanelli: michele.fanelli@studbocconi.it Federico Lazzarini: federico.lazzarini@studbocconi.it Rolf Minardi: rolf.minardi@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

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.

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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 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) timeseries 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 abovementioned 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=supx|(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:

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

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%}	-2.86%	-3.13%
VaR _{99%}	-4.24%	-4.84%
ES _{95%}	-4.12%	-4.56%
ES _{99%}	-4.89%	-5.38%

	VaR 95	VaR 99	ES 95	ES 99
VISA	-1.16%	-1.68%	-1.48%	-1.94%
COCA-COLA CO	-1.19%	-1.71%	-1.51%	-1.99%
VINCI	-1.22%	-1.78%	-1.57%	-2.09%
CENCORA	-1.23%	-1.85%	-1.61%	-2.19%
WASTE MANAGEMENT	-1.25%	-1.86%	-1.63%	-2.19%
	VaR 95	VaR 99	ES 95	ES 99
WORDLINE	-7.86%	-11.11%	-9.86%	-12.79%
SOLAREDGE TECH.	-7.87%	-12.28%	-10.67%	-15.36%
MAERSK	-10.37%	-14.64%	-12.99%	-16.84%
ROLLS-ROYCE HOLDINGS	-10.82%	-15.37%	-13.61%	-17.69%
ROCHE HOLDING	-10.98%	-15.64%	-13.84%	-18.04%

TOP & BOTTOM 5 stocks (simple approach)



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%}	-3.05%	0.34%
VaR _{99%}	-4.31%	0.40%
ES _{95%}	-4.22%	0.35%
ES _{99%}	-4.83%	0.42%

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)
IBERDROLA	-1.45%	-2.84%	-2.41%	-3.39%
CATALENT INC	-1.38%	-2.88%	-2.48%	-3.91%
HILTON HOLDINGS	-1.60%	-3.19%	-2.71%	-4.03%
CENCORA	-1.76%	-3.86%	-3.34%	-5.93%
STELLANTIS	-2.04%	-4.33%	-3.72%	-6.44%

	VaR 95 (GARCH)	VaR 99 (GARCH)	ES 95 (GARCH)	ES 99 (GARCH)
WATCHES OF SWITZ GR	-8.17%	-11.37%	-9.20%	-13.04%
SOLAREDGE TECH.	-9.02%	-12.81%	-10.78%	-16.98%
OCADO GROUP	-10.80%	-15.07%	-12.34%	-17.54%
HELLOFRESH (XET)	-11.86%	-17.32%	-15.89%	-18.09%
NOVO NORDISK	-13.22%	-18.11%	-16.96%	-22.06%

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