Risk Management Project

Ferdinando de Martino, Carlo Eterno, Antonino Gandolfo, Riccardo Martelli, Tommaso Tomellini

Milan's Polytechnic – Graduate School of Management

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Abstract

In this project, we analyze the performance and risk/return profile of various investment funds, assessing the impact of volatility and Value at Risk on the portfolio using the Cornish-Fisher expansion for more realistic estimates. Additionally, return scenarios and risk classes are evaluated according to the PRIIPs regulation.

Contents

Requests

In this project, the following activities are required:

1. Display, with clear and organized charts, the price evolution of each fund and calculate their returns.

2. Calculate summary statistics for each fund, including mean, standard deviation, skewness, and kurtosis, in addition to returns and volatility across different time windows (e.g., daily, monthly, and annual). Additionally, estimate the correlation matrix between the funds, if possible including significance tests.

3. Calculate the Value at Risk (VaR) for each fund using at least one of the following methodologies: historical, parametric-Gaussian, or historical simulation.

4. Construct and analyze a portfolio composed of the funds under examination, using the indicated weights and considering liquidity as a risk-free asset with zero volatility. Simulate an investment of 100,000 euros made three years ago and observe its evolution, calculate the portfolio's daily volatility, estimate the VaR using at least two methodologies and compare the results. Additionally, assess the diversification of the portfolio using the correlation matrix.

5. Apply the KID/PRIIPs regulation by calculating, for each fund:

    - The favorable, moderate, and unfavorable return scenarios, without performing additional stress tests.
    - The synthetic market risk indicator (MRM), expressed as a class from 1 to 7, according to the PRIIPs regulation.

Introduction

This project focuses on a detailed assessment of the performance of the listed funds, with particular attention to estimating the risk exposure of a portfolio composed of these funds.
Two equally weighted portfolio compositions have been evaluated, in which all funds have the same wealth allocation given by $w = \frac{1}{N}$, along with a case considering a distribution of wealth according to the following weight vector:

Funds	**Portfolio Weight**
SGR Emerging Markets	10%
SGR Global	20%
SGR Italy	10%
SGR Global Dynamic Strategy	10%
SGR Short Term	10%
SGR Performance	10%
SGR Far East	20%
Liquidity	10%

Table 1: Portfolio composition

The liquidity component is to be considered as an asset that does not exhibit any correlation with the funds. For performance evaluation purposes, liquidity is treated as a "*risk-free*" asset with returns following the **US Treasury 3M**.
The number of price observations available for the study is uneven, resulting in different levels of reliability and robustness in the calculations performed.
Funds with fewer data points will have statistics that are more closely aligned with the current financial context, highlighting their responsiveness to market shocks ; however, they will also be more exposed to a higher degree of uncertainty in the estimation of statistical measures such as returns and standard deviation. As a consequence, interpretations of the results will be presented while taking into account the effects of high granularity in some historical price series.
Below is a summary table of the available data points. The data represent the daily closing prices of the funds recorded in the markets.

Funds	**Non-Null Count**	**Years**
SGR Emerging Markets (EM)	2512	9
SGR Global (GL)	2512	9
SGR Italy (IT)	2512	9
SGR Global Dynamic Strategy (LA)	2512	9
SGR Short Term (LI)	2512	9
SGR Performance (MO)	2512	9
SGR Far East (PA)	2512	9
SGR Special (PE)	1936	7
SGR Savings (RI)	590	2
SSC Growth Strategy (SC)	590	2
SGR Moderate Strategy (SM)	590	2

Table 2: Data count and duration in years (252 days/year)

1 Analysis of Fund Price Trends and Returns

In this section, we analyze the price trends of the various funds and their returns.

1.1 SGR Emerging Markets (EM)

This fund has a long historical series and has achieved a total return of 61% since the beginning of the observations. More pronounced tails are evident, particularly on the left side. Notably, there was a price drop at the beginning of 2020 due to the impact of COVID, followed by a strong rebound driven by recovery policies aimed at boosting the economy, such as interest rate cuts by central banks.

The following images show that the logarithmic returns of the fund do not closely follow a Gaussian pattern. More pronounced tails are evident, particularly on the left side. This indicates a leptokurtic and slightly asymmetric distribution: the high kurtosis reflects the presence of extreme events occurring more frequently than expected, while the skewness suggests that extreme negative returns tend to be more likely than extreme positive ones.

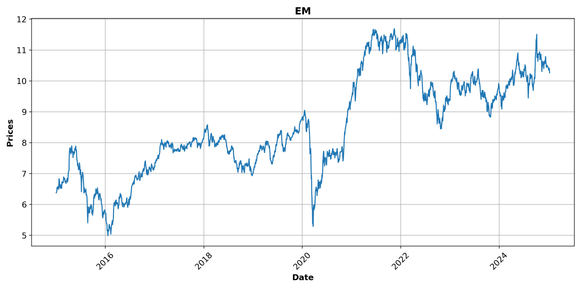


Figure 1: Prices of SGR Emerging Markets (EM)

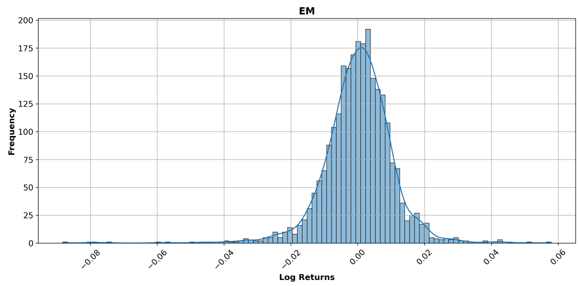
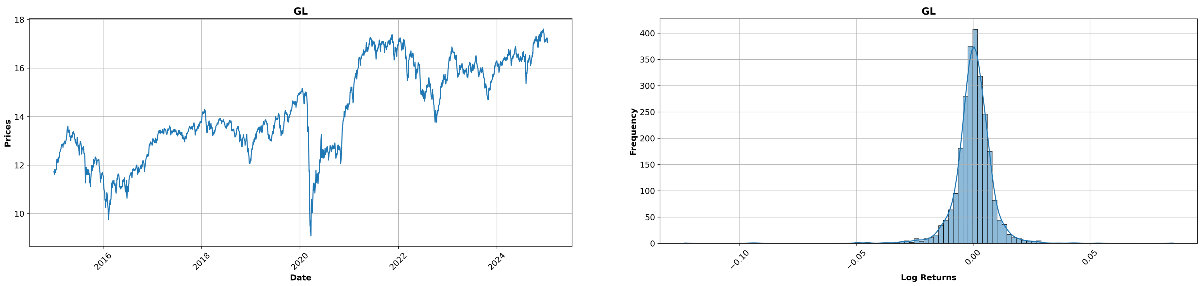


Figure 2: Log Returns of SGR Emerging Markets (EM)

1.2 SGR Global (GL)

Similar to the previous case, the price trend was affected by the COVID crisis in 2020 and the subsequent economic rebound. Since the beginning of the observations, it has achieved a total return of 45.48%.

Unlike the previous distribution, the SGR Global fund shows a higher concentration of values around zero, indicating that the fund is more diversified compared to the Emerging Markets fund.



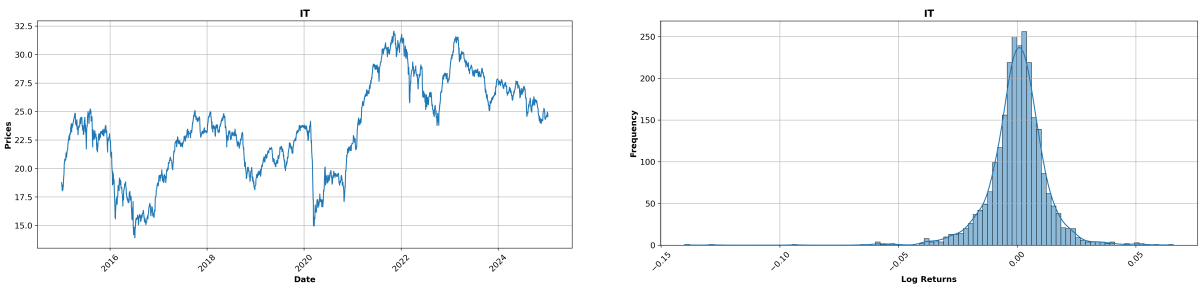
(a) Price evolution of SGR Global (GL) (b) Logarithmic returns of SGR Global (GL)

Figure 3: Price evolution and logarithmic returns of SGR Global (GL).

1.3 SGR Italy (IT)

The Italian case shows a less regular price trend compared to the previous funds, with more reactive movements during the COVID crisis and the subsequent phase of economic stimulus. Its total return since the beginning of the observations is 30.94%.

As evidence of the above, the logarithmic returns deviate further from the assumption of normality, likely due to the fund's higher concentration in highly correlated securities.



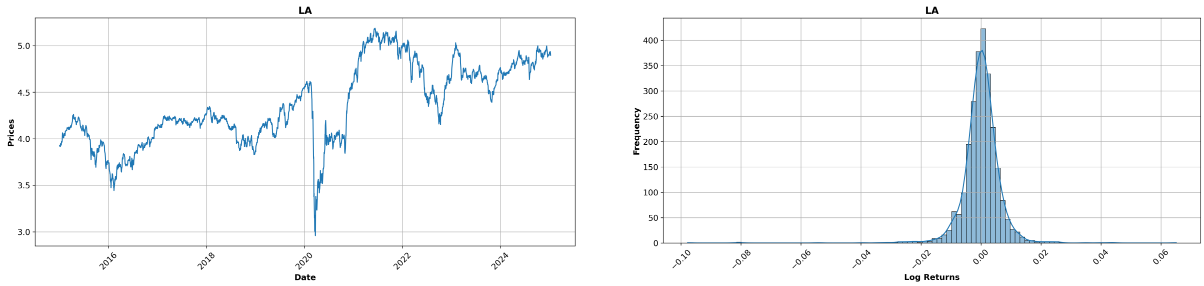
(a) Price evolution of SGR Italy (IT) (b) Logarithmic returns of SGR Italy (IT)

Figure 4: Price evolution and logarithmic returns of SGR Italy (IT).

1.4 SGR Global Dynamic Strategy (LA)

The SGR Global Dynamic Strategy fund shows trends in line with those already analyzed. Its total return since the beginning of the observations is 24.76%.

Also in this case, the returns are highly centered and close to zero, with persistent signs of leptokurtosis and asymmetry.



(a) Price evolution of SGR Global Dynamic Strategy (LA)

(b) Logarithmic returns of SGR Global Dynamic Strategy (LA)

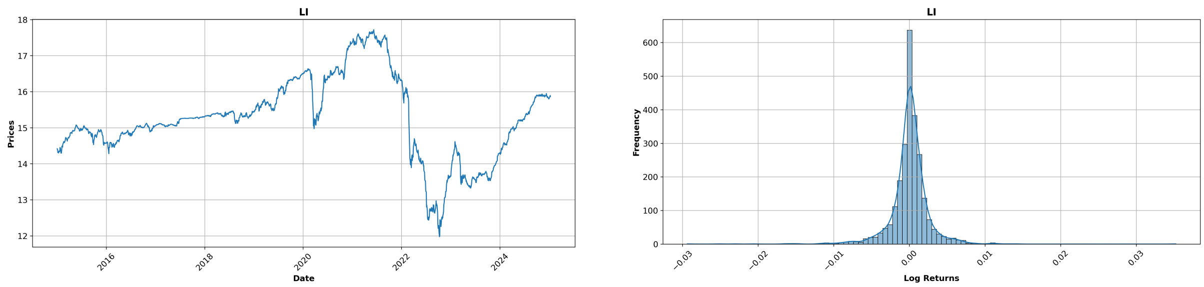
Figure 5: Price evolution and logarithmic returns of SGR Global Dynamic Strategy (LA).

1.5 SGR Short Term (LI)

In this case, the price dynamics of the fund are significantly different compared to the others. Although there was a brief period of retracement due to the COVID crisis, a reactive recovery appears to have followed. Subsequently, at the beginning of 2022, there was a pronounced period of price decline attributable to the strong geopolitical instability that characterized that year.

Its total return since the beginning of the observations is 10.04%.

Compared to the funds already analyzed, the SGR Short Term fund shows a more balanced distribution with a slight right skew in the distribution of returns.



(a) Price evolution of SGR Short Term (LI)

(b) Logarithmic returns of SGR Short Term (LI)

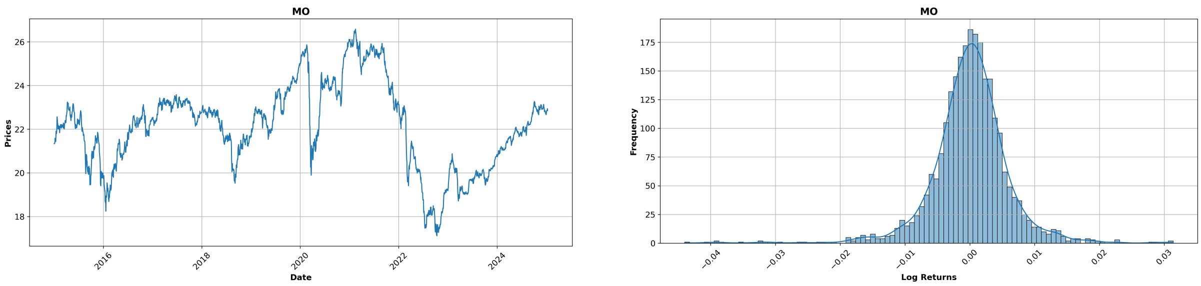
Figure 6: Price evolution and logarithmic returns of SGR Short Term (LI).

1.6 SGR Performance (MO)

This fund, like the SGR Short Term fund, also shows a price evolution characterized by a sharp reaction to the political instability of 2022. In this case, the bearish effects appear to have impacted the fund's price more significantly.

Its total return since the beginning of the observations is 7.08%.

In this case, the distribution of log-returns shows a higher standard deviation, resulting in a less concentrated distribution of returns.



(a) Price evolution of SGR Performance (MO)

(b) Logarithmic returns of SGR Performance (MO)

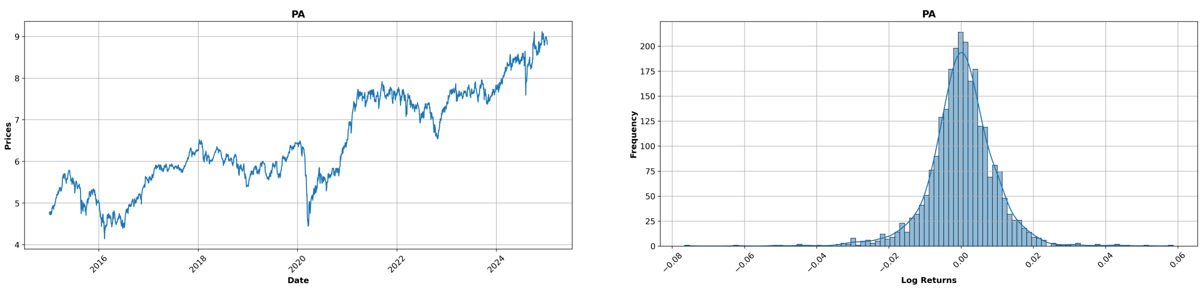
Figure 7: Price evolution and logarithmic returns of SGR Performance (MO).

1.7 SGR Far East (PA)

This fund stands out for having the best performance, in terms of total return, within the considered pool, and its price trend shows a significant response to the financial stimuli previously observed.

Its total return since the beginning of the observations is 85.21%.

As in the previous case, the distribution of log-returns shows a higher standard deviation, resulting in a less concentrated distribution of returns.



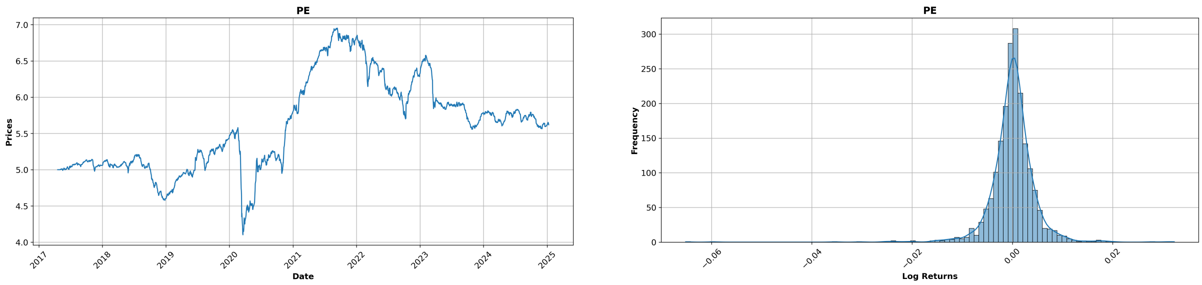
(a) Price evolution of SGR Far East (PA)

(b) Logarithmic returns of SGR Far East (PA)

Figure 8: Price evolution and logarithmic returns of SGR Far East (PA).

1.8 SGR Special (PE)

The SGR Special fund, despite a retracement due to the COVID crisis, showed an excellent recovery and seems to have maintained strong dynamism in the subsequent market scenarios. Its total return since the beginning of the observations is 12.4%.
In this case, the fund again shows a strong concentration of returns around the central value and a pronounced asymmetry on the left side of the distribution curve.

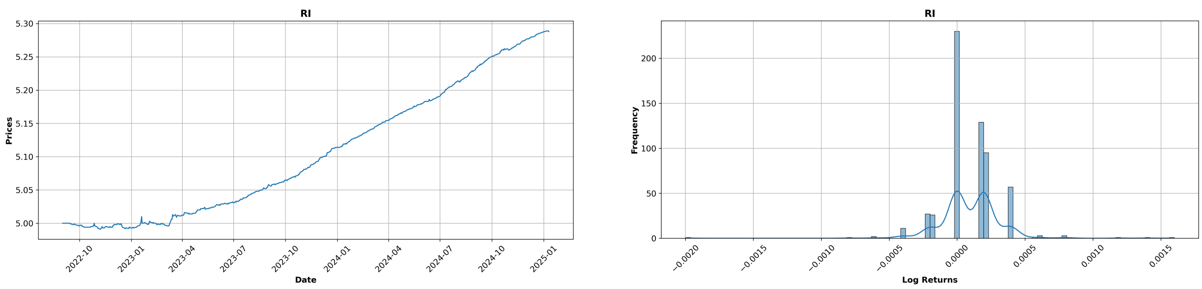


(a) Price evolution of SGR Special (PE) (b) Logarithmic returns of SGR Special (PE)

Figure 9: Price evolution and logarithmic returns of SGR Special (PE).

1.9 SGR Savings (RI)

The SGR Savings fund, along with the subsequent ones, has an extremely small historical price series, showing a steadily increasing monotonic trend.
Its total return since the beginning of the observations is 5.76%.
The distribution of returns does not resemble a Gaussian curve at all; on the contrary, the returns appear to be distributed over values that can be defined as "standard" for this fund.



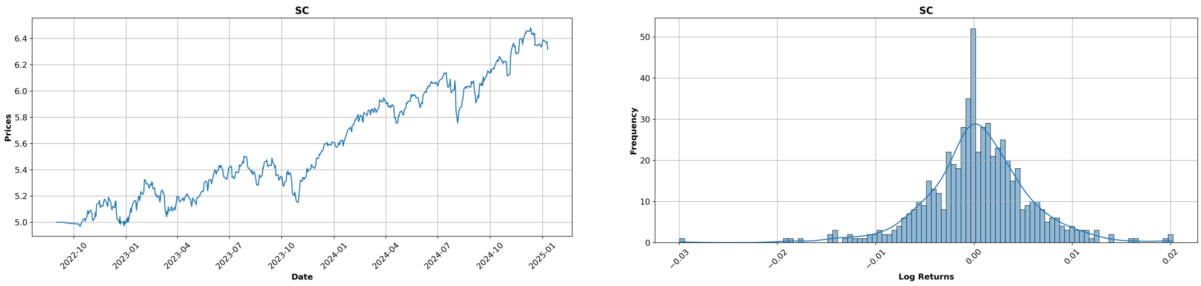
(a) Price evolution of SGR Savings (RI) (b) Logarithmic returns of SGR Savings (RI)

Figure 10: Price evolution and logarithmic returns of SGR Savings (RI).

1.10 SSC Growth Strategy (SC)

Similar to the previous fund, this one has a limited database of approximately 3 years of daily observations. Compared to the previous case, it appears to have a more typical price dynamic. Its total return since the beginning of the observations is 26.32%.

Although the distribution of logarithmic returns is still far from Gaussian, in this case we observe a more homogeneous distribution of returns, with an asymmetry on the left tail.



(a) Price evolution of SSC Growth Strategy (SC)

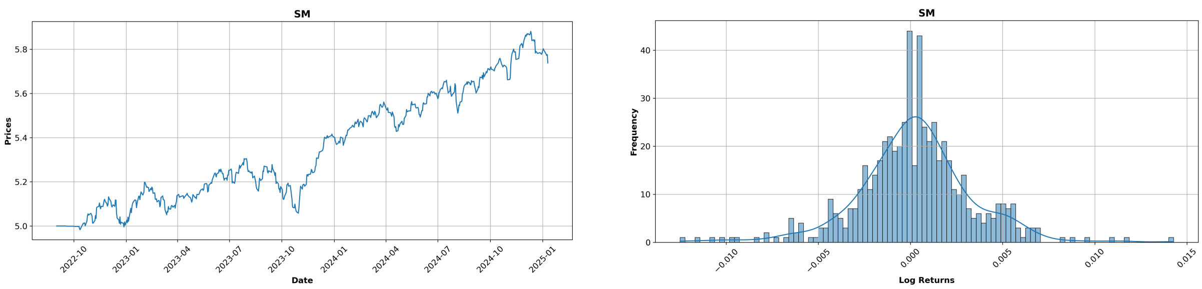
(b) Logarithmic returns of SSC Growth Strategy (SC)

Figure 11: Price evolution and logarithmic returns of SSC Growth Strategy (SC).

1.11 SGR Moderate Strategy (SM)

As with the previous fund, a similar trend in the price evolution of the fund is confirmed. Its total return since the beginning of the observations is 14.76%.

Also in this case, the assumption of a Gaussian distribution for the logarithmic returns is far from the observed reality. Here, we observe a distribution with less asymmetry.



(a) Price evolution of SGR Moderate Strategy (SM)

(b) Logarithmic returns of SGR Moderate Strategy (SM)

Figure 12: Price evolution and logarithmic returns of SGR Moderate Strategy (SM).

Below is a summary table of the total returns of the funds:

Fund	**Value**	**Observation Period**
SGR Far East (PA)	85.22%	2015–2025
SGR Emerging Markets (EM)	61.01%	2015–2025
SGR Global (GL)	45.49%	2015–2025
SSC Growth Strategy (SC)	26.32%	2015–2025
SGR Italy (IT)	30.94%	2015–2025
SGR Global Dynamic Strategy (LA)	24.76%	2015–2025
SGR Moderate Strategy (SM)	14.76%	2015–2025
SGR Special (PE)	12.40%	2017–2025
SGR Short Term (LI)	10.05%	2022–2025
SGR Performance (MO)	7.09%	2022–2025
SGR Savings (RI)	5.76%	2022–2025

Table 3: Total returns of the funds over the observed period

2 Summary Statistics

Below are the return and volatility values for the various funds across different time windows. These evaluations were performed backward, from the last available observation backward to the reference value of the observation window.

In general, as shown in Table 4, the *1D* and *1M* columns display a negative average return, reflecting a period of market contraction, likely due to the ongoing trade tariff wars. Over the long term, the averages confirm what was observed when looking at the price evolution dynamics. Notably, there are two cases with negative one-year returns: for the Italy fund and the SGR Special fund.

Fondo	1D	1M	1Y
EM	-1.02	-2.87	6.94
GL	-0.901	-2.39	5.24
IT	-1.07	-0.983	-11.1
LA	-0.528	-0.830	3.64
LI	-0.189	-0.170	10.9
MO	-0.397	-0.44	9.63
PA	-0.283	-1.40	13.1
PE	-0.319	0.303	-2.68
RI	-1.89×10^{-2}	0.208	3.36
SC	-0.894	-2.15	12.7
SM	-0.658	-2.18	6.59

Table 4: Returns of periods (%)

Table 5 also confirms what is shown in the plots of logarithmic returns: wider "bell curves" are associated with higher volatility values. Additionally, there is a slight increase in short-term volatility compared to long-term volatility, confirming a more turbulent period in the markets.

Table 5: Period Volatility

Fund	1D	1M	1Y
EM	1.04×10^{-2}	9.23×10^{-3}	9.83×10^{-3}
GL	8.49×10^{-3}	6.77×10^{-3}	7.70×10^{-3}
IT	1.24×10^{-2}	1.06×10^{-2}	1.19×10^{-2}
LA	6.73×10^{-3}	5.22×10^{-3}	5.97×10^{-3}
LI	2.70×10^{-3}	1.93×10^{-3}	2.38×10^{-3}
MO	5.99×10^{-3}	5.20×10^{-3}	6.02×10^{-3}
PA	9.30×10^{-3}	8.42×10^{-3}	8.82×10^{-3}
PE	4.76×10^{-3}	3.67×10^{-3}	4.72×10^{-3}
RI	2.27×10^{-4}	1.98×10^{-4}	2.76×10^{-4}
SC	5.30×10^{-3}	5.07×10^{-3}	5.39×10^{-3}
SM	3.08×10^{-3}	2.96×10^{-3}	3.18×10^{-3}

2.1 Correlation Matrix

Based on the heterogeneity of the datasets for the historical series of the funds, three correlation matrices have been proposed to highlight the relationships in the price dynamics among the various funds. In particular, the following have been evaluated:

1. A matrix among the funds with the highest number of observations.
2. A matrix including the funds with the lowest number of observations.
3. A matrix that considers all the funds.

The correlation matrix among the funds with the largest number of observations shows that the assets *[EM, GL, IT, LA]* exhibit a high level of positive correlation, particularly between LA and GL. On average, the correlation between these assets and the remaining ones *[LI, MO, PA]* appears to be lower.

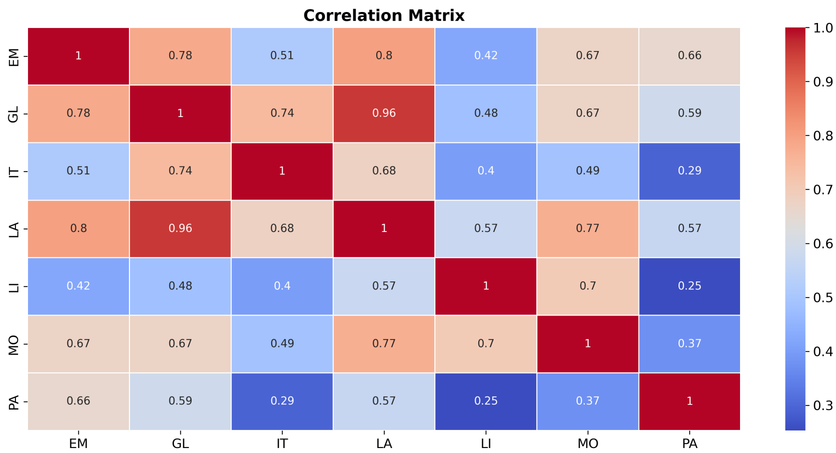


Figure 13: Correlation matrix of high-sample funds.

Among the assets with the lowest number of observations, a very strong correlation is observed between *[SC, SM]*.

When examining the correlation matrix that includes all the assets, it can be seen that the RI fund is much less correlated with the other funds compared to all the others. In contrast, the pairs *[LA, GL]* and *[SC, SM]* exhibit a very strong correlation.

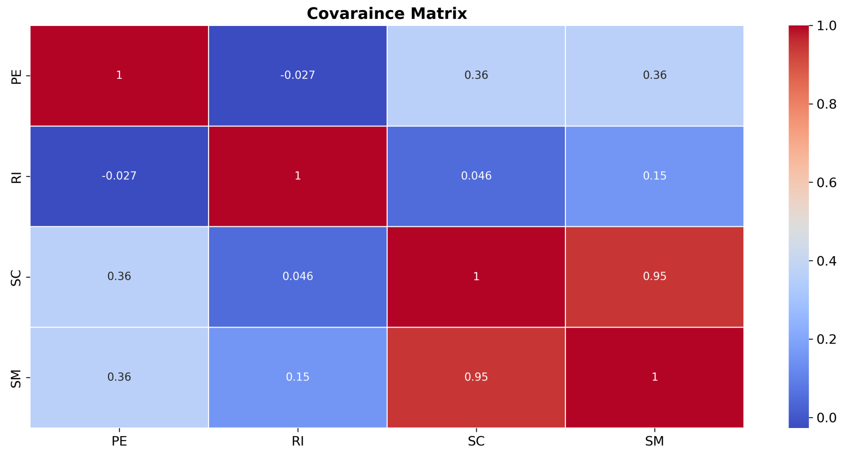


Figure 14: Correlation matrix of small-sample funds.

The reliability test of the correlation matrix shows that the assets with fewer observations may not provide reliable correlation values. Even the "EM" fund generally exhibits high levels of p_value, making these measures less reliable.

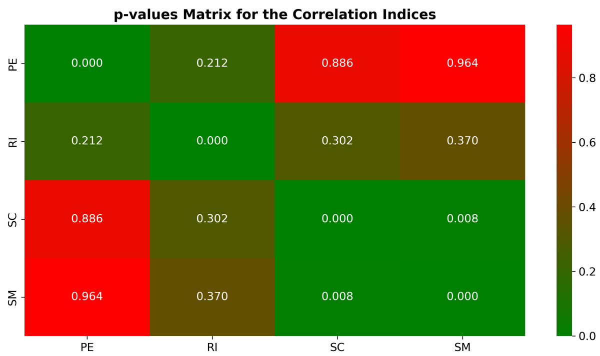


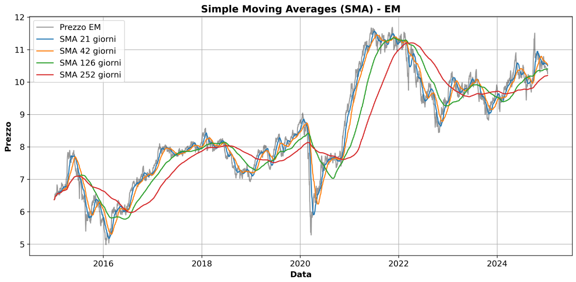
Figure 15: P-value test of the correlation matrix.

2.2 Moving Average

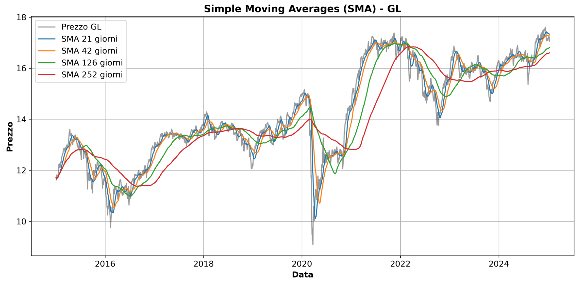
In the chart we have created, in addition to the price trends, we included three moving averages: a 20-day (short-term), an 80-day (medium-term), and a 200-day (long-term) moving average. Moving averages are widely used tools in finance because they help to "smooth out" price movements and better understand the overall market trend by filtering out some of the background noise.

The 20-day moving average follows the price very closely and therefore reacts more quickly to changes. The 80-day moving average is slightly slower and provides an intermediate perspective, while the 200-day moving average is the slowest and helps to understand the long-term direction. When these lines cross each other, they often signal a potential trend reversal: for example, if the fast-moving average (20-day) crosses above the 200-day moving average, it can indicate that the market is strengthening.

Conversely, if it crosses below, it may signal weakness. It is important to remember, however, that these signals always come with some delay, as moving averages are based on past data. Below, for each fund, are the corresponding charts:

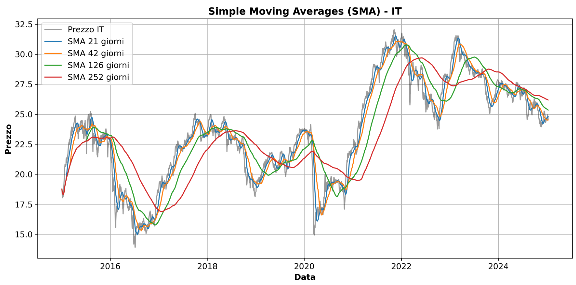


(a) SMA Price EM

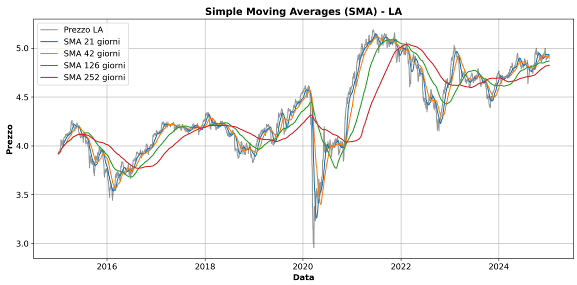


(b) SMA Price GL

Figure 16: Simple Moving Average applied to EM and GL price series.

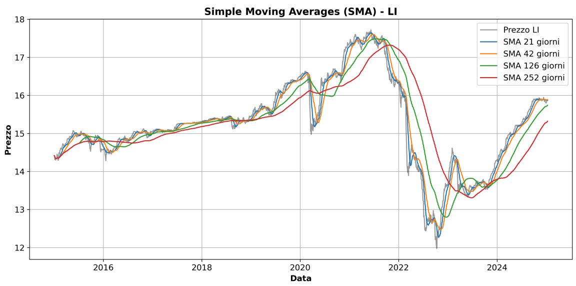


(a) SMA Price IT

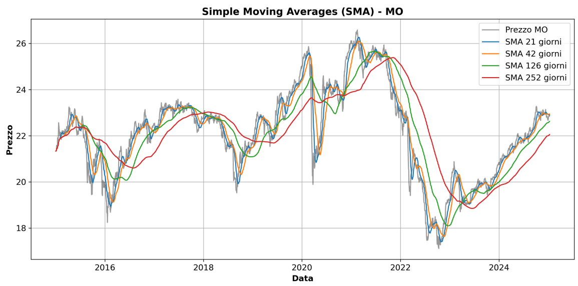


(b) SMA Price LA

Figure 17: Simple Moving Average applied to IT and LA price series.

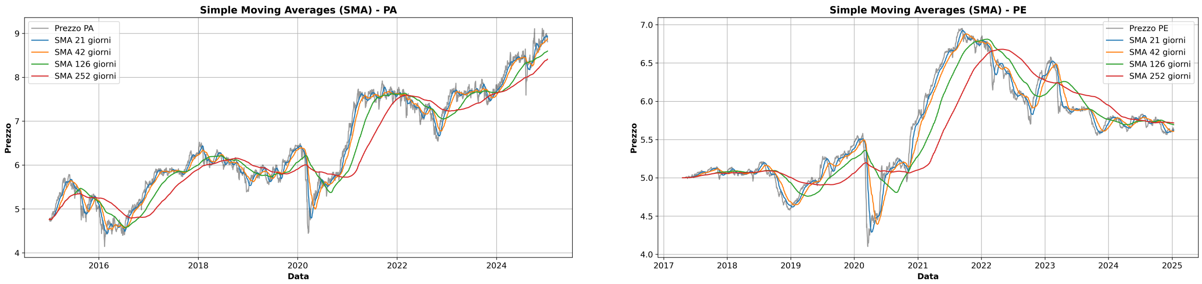


(a) SMA Price LI



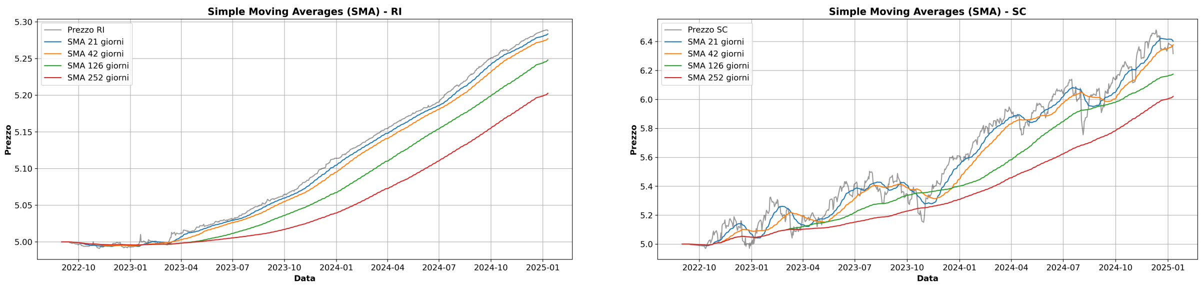
(b) SMA Price MO

Figure 18: Simple Moving Average applied to LI and MO price series.



(a) SMA Price PA (b) SMA Price PE

Figure 19: Simple Moving Average applied to PA and PE price series.



(a) SMA Price RI (b) SMA Price SC

Figure 20: Simple Moving Average applied to RI and SC price series.

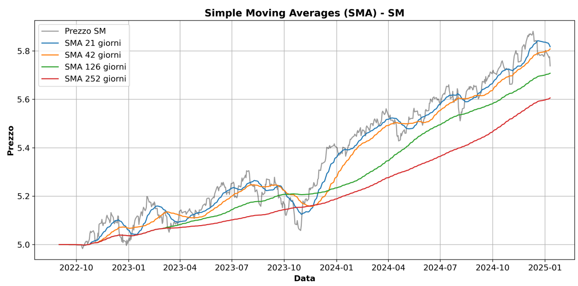


Figure 21: Simple Moving Average applied to SM price series

3 Value at Risk

In the following section, the Value at Risk (VaR) of the individual funds and subsequently of the composed portfolio as described above is evaluated.

VaR represents a statistical measure corresponding to the loss that is expected for a given probability value defined at a confidence level alpha.

$$VaR_\alpha(X) = \inf \{x \in \mathbb{R} : P(X \leq x) \geq \alpha\}$$

The methods used to evaluate VaR included historical series analysis and the parametric method, which assumes normally distributed returns for the calculation, using the mean and standard deviation to estimate the percentile corresponding to the alpha value.

$$VaR_\alpha(X) = \mu + \sigma \cdot z_\alpha$$

The two methods were considered to highlight how the parametric method, which relies on a strong theoretical assumption, can differ from the ex-post evaluation using historical series, which is more reliable in the case of a large number of observations. Through Table 6, it is possible to note that in some cases, deviations from the historical value of up to 38% in percentage terms are observed.

Table 6: Confronto tra metodi di calcolo del VaR per fondo

Fondo	**Historic (%)**	**Gaussian (%)**	**Delta (%)**
EM	-1.504	-1.691	12.467
GL	-1.167	-1.381	18.368
IT	-1.904	-2.026	6.400
LA	-0.888	-1.099	23.703
LI	-0.381	-0.441	15.816
MO	-0.885	-0.983	11.123
PA	-1.410	-1.504	6.697
PE	-0.594	-0.777	30.797
RI	-0.020	-0.028	38.987
SC	-0.776	-0.833	7.235
SM	-0.447	-0.483	8.009

3.1 Portfolio Performance

The analysis continues by considering a portfolio composed of risky financial instruments plus a risk-free asset, with the weights reported in Table 1. Based on this composition, the evolution of an investment of €100,000 made over a period of 3 years is observed:

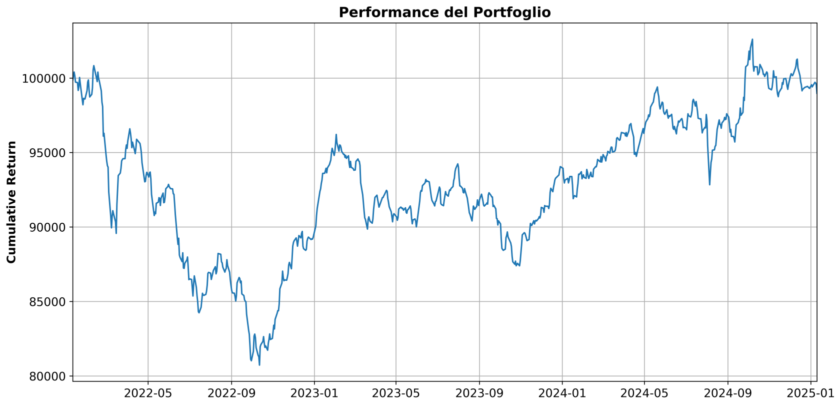


Figure 22: Portfolio performance

An initial sharp decline is observed during the first 10 months, followed by a subsequent recovery; however, the investment ends with a loss, with a final value of €98,981.40, corresponding to a variation of -1.02%.

Volatility, recorded on a daily basis, was calculated using both simple moving averages and exponential moving averages. By comparing the methods, it can be noted that the exponential moving average method shows more pronounced volatility spikes.

3.2 Portfolio VaR

Also in this case, the portfolio's VaR was evaluated using the two methodologies mentioned above, highlighting that the parametric estimation proves to be more pessimistic than the historical one. This is demonstrated by the slight asymmetry in the distribution of the logarithmic returns towards the left tail of the distribution, as can be observed in Figure 7.

Table 7: Comparison between VaR calculation methods

Metodo	**VaR**	**Perdita attesa (€)**
Historical VaR	-0,74	73 572,68
Gaussian VaR	-0,80	80 231,15

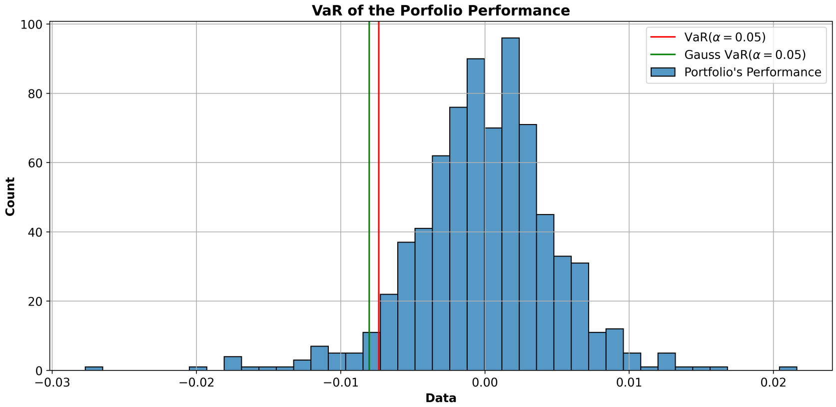


Figure 23: Portfolio VaR

3.3 Portfolio Returns and Volatility

The portfolio exhibited high volatility, particularly between 2022 and 2023, with strong daily fluctuations in returns. A peak of instability occurred in August 2024 due to tensions related to Japanese carry trading. Despite an overall loss of 4.2%, the strategy managed to limit losses during critical periods.

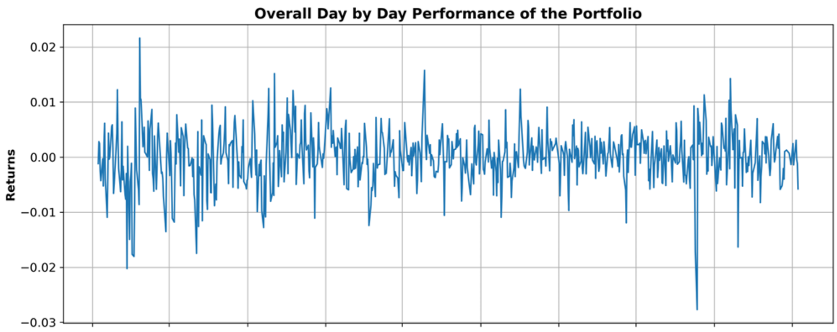


Figure 24: Portfolio returns

The portfolio exhibited high volatility, particularly between 2022 and 2023, with significant daily fluctuations in returns. A peak in instability occurred in August 2024 due to tensions related to Japanese carry trading. Despite an overall loss of 4.2%, the strategy managed to limit damage during critical moments.

The volatility analysis using the EMA highlights rapid reactions and sudden spikes, while the rolling window shows slower and more persistent trends. Between 2022 and 2023, the EMA captured individual market shocks, while the rolling window indicated a consistent turbulence. In 2024, both analyses show a reduction in volatility but with different nuances: the EMA indicates a better responsiveness of the portfolio to shocks. At the beginning of 2025, both methods converge towards a phase of stability. This dual perspective reveals how the portfolio has learned to manage risk more effectively.

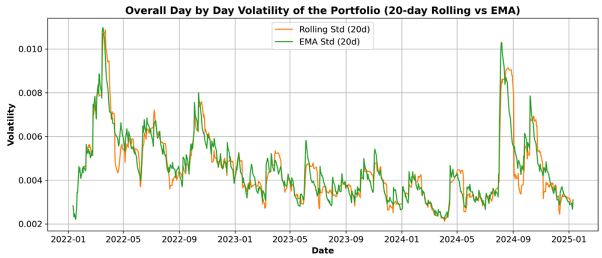


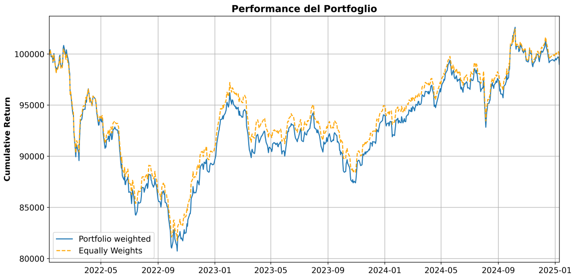
Figure 25: Portfolio Volatility

3.4 Diversification Analysis

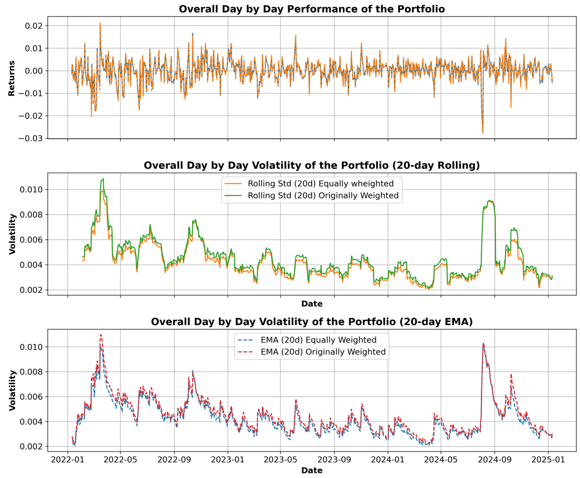
At this point, we represent the correlation matrix through a heatmap, as shown in Figure 4, to provide an immediate view of the portfolio's level of diversification. The heatmap displays "dark" areas, indicating correlations close to zero or negative values. However, it is possible to observe a light-colored area in the upper right corner, indicating that among those funds, the correlation is close to 1. In conclusion, the portfolio does not exhibit a high level of diversification, although the correlation between some funds is negative.

3.5 Discussion about Equally Weighted Portfolio

As shown in Figure 26, the return of the equally weighted portfolio is, on average, higher than that of the portfolio composed using the weight vector w. On the other hand, observing Figure 9, it is evident that the volatility of the portfolio with weights w is generally higher than that of the equally weighted portfolio. These observations lead us to conclude that the equally weighted portfolio exhibits better diversification compared to the portfolio using weights w. The latter, by overweighting securities with higher correlations, generates a higher average return while sacrificing volatility levels.



(a) Portfolios Performance



(b) Portfolios LogReturns and Volatility

Figure 26: Portfolio performance and associated log-returns with volatility.

4 PRIIPs Normative

In the context of preparing Key Information Documents (KIDs) for PRIIP products, European regulations require that the product's risk/return profile be presented clearly and understandably for retail investors. Within this framework, the activity carried out involved implementing an automated calculation process aimed at estimating:

1. The performance scenarios (favorable, moderate, and unfavorable);
2. The synthetic market risk indicator (MRM), expressed as a class from 1 to 7.

4.1 Structure

The starting point is a dataset containing the daily log-returns of various investment funds. The data were processed to remove null values and to consider only those funds with at least 5 years of observations, in line with the minimum frequency required for meaningful statistical analyses (approximately 1,260 data points per fund).

4.2 Statistical Processing

For each fund, the key statistical moments necessary to capture the actual characteristics of the distribution—which, in financial markets, often deviates from the assumption of normality—were calculated:

1. The mean (μ) of the returns;
2. The standard deviation (σ) of the returns;
3. Skewness;
4. Excess kurtosis.

4.3 Scenario Analysis

According to **Annex V of Regulation (EU) 2017/653**, investors must be provided with at least three scenarios:

- **Favorable scenario** (90^{th} percentile),
- **Moderate scenario** (50^{th} percentile),
- **Unfavorable scenario** (10^{th} percentile).

These scenarios represent the potential evolution of the product's value at the end of the recommended holding period, net of costs, providing a realistic view of how the fund might perform under different market conditions.

We used the Cornish-Fisher expansion to estimate the quantiles corresponding to the indicated percentiles more accurately. Instead of using the standard normal distribution, the Cornish-Fisher method was applied. This approach has the advantage of adjusting the normal quantile by taking into account *skewness* and *kurtosis*, two characteristics often present in financial returns that make the distribution non-symmetric.

The formula used is as follows:

$$z_{CF} = z + \frac{(z^2 - 1)}{6}S + \frac{(z^3 - 3z)}{24}K - \frac{(2z^3 - 5z)}{36}S^2 \tag{1}$$

where:

- z is the quantile of the normal distribution (e.g., ± 1.28 for the 10^{th} and 90^{th} percentiles),
- S is the skewness,
- K is the excess kurtosis,
- z_{CF} is the adjusted quantile.

This formula allows for a more realistic estimation of potential losses or gains under favorable and unfavorable conditions, thereby improving the representation of the risk/return profile for the investor.

4.4 Market Risk Measure (MRM)

Another element required by the regulation is the classification of market risk using the synthetic Market Risk Measure (MRM). This indicator is based on the **volatility equivalent to the Value at Risk (VaR)** at a 97.5% confidence level.
Specifically:

- The adjusted quantile of the log-returns is estimated using the Cornish-Fisher expansion;
- This value is converted into a percentage return;
- The result is expressed as a potential loss and transformed into **annualized volatility**.

Finally, each fund is assigned a **class from 1 to 7**, according to the scale defined in **Annex II of the Regulation**, which associates each level of volatility with an increasing risk class.

4.5 Risultati e Osservazioni

The results for each fund are reported below. For each asset, the expected performance under the three scenarios (favorable, moderate, and unfavorable) has been estimated, along with the potential loss in the event of a market shock (VaR 97.5%), and the corresponding MRM class assignment.

Classes	**Equivalent Volatility**
1	$< 0,5\%$
2	$0,5\%$ – 5%
3	5% – 12%
4	12% – 20%
5	20% – 30%
6	30% – 80%
7	$\geq 80\%$

Table 8: Classes of Risk Based on Equivalent Volatility

4.6 Analysis of Individual Funds

Fund EM

- Favorable scenario: $+0.67\%$
- Moderate scenario: $+0.01\%$
- Unfavorable scenario: -0.84%
- VaR 97.5%: 2.91%

The fund shows good stability, with a contained potential loss and symmetric scenarios. **Class 3** (moderate risk).

Fund GL

- Favorable scenario: -1.11%
- Moderate scenario: $+0.01\%$
- Unfavorable scenario: $+0.75\%$
- VaR 97.5%: 4.04%

The anomalous results in the extreme scenarios (negative favorable, positive unfavorable) suggest a strong distortion in the distribution of returns. Nevertheless, volatility remains moderate. **Class 3** (moderate risk).

Fund IT

- Favorable scenario: $+0.22\%$
- Moderate scenario: $+0.00\%$
- Unfavorable scenario: -0.57%
- VaR 97.5%: 4.08%

The fund shows a regular behavior, with a symmetric risk/return profile and a VaR consistent with the category average. **Class 3** (moderate risk).

Fund LA

- Favorable scenario: -1.14%
- Moderate scenario: $+0.01\%$
- Unfavorable scenario: $+0.81\%$
- VaR 97.5%: 3.42%

Similar to GL, it presents an anomalous structure in the extremes. This may be due to isolated events or pronounced asymmetries. **Class 3** (moderate risk).

Fund LI

- Favorable scenario: -0.20%
- Moderate scenario: $+0.00\%$
- Unfavorable scenario: $+0.16\%$
- VaR 97.5%: 1.11%

Deeply conservative, with returns concentrated around zero and very low volatility. **Class 2** (low risk).

Fund MO

- Favorable scenario: $+0.41\%$
- Moderate scenario: $+0.00\%$
- Unfavorable scenario: -0.50%
- VaR 97.5%: 1.64%

Similar to LI, it shows stability and low dispersion in returns. **Class 2** (low risk).

Fund PA

- Favorable scenario: $+0.77\%$
- Moderate scenario: $+0.02\%$
- Unfavorable scenario: -0.80%
- VaR 97.5%: 2.34%

Regular behavior, with moderate volatility and good potential margins. **Class 3** (moderate risk).

Fund PE

- Favorable scenario: -0.62%
- Moderate scenario: $+0.00\%$
- Unfavorable scenario: $+0.37\%$
- VaR 97.5%: 2.25%

A negative favorable scenario and a positive unfavorable scenario indicate a likely distortion. However, the calculated risk remains within the average range. **Class 3** (moderate risk).

Fund RI

The fund does not have a sufficient number of observations (less than 5 years), making it impossible to reliably estimate the scenarios and VaR. In these cases, a provisional classification based solely on simple volatility is recommended, or exclusion from the scope of the analysis. **Class 3** (moderate risk).

4.7 Final Remarks on the Funds and Qualitative Risk Ranking

The analysis conducted reveals a clear risk hierarchy among the considered funds. Although most of the funds fall within a medium-low risk range, some interesting differences emerge that are worth highlighting also from a qualitative perspective.
At the top of the ranking in terms of stability are the LI and MO funds, both with an MRM Class of 2, reflecting low volatility and returns tightly clustered around zero. These funds exhibit a conservative behavior, suitable for those seeking capital protection rather than returns.

Following in the intermediate band are funds such as EM, IT, PA, and PE, all classified as Class 3, with moderate expected losses and fairly balanced return profiles. These products are suitable for investors with a moderate risk appetite, seeking stable yet contained growth.
Some funds, particularly GL and LA, while also classified under Class 3, exhibit more irregular behaviors in the data, with inverted or anomalous scenarios. This suggests the presence of "hidden" volatility, likely due to sporadic events or highly asymmetric return distributions. From a prudent perspective, these funds should be monitored more closely.
Finally, the RI fund could not be fully evaluated due to insufficient data. The lack of a sufficient historical record limits the ability to accurately estimate the risk, and it is advisable to treat it with caution during evaluation.
In summary, the overall landscape shows a rather balanced distribution, with no extremely risky funds. However, there are relevant nuances among the various securities that can be decisive in the selection process for a conscious investor.

Conclusions

The entire procedure proved to be consistent with the provisions of EU Regulation 2017/653. The results obtained were useful in describing the expected behavior of the funds under three market conditions (favorable, moderate, unfavorable) and in estimating the maximum expected loss using the appropriate statistical approach.

The analysis was conducted assuming a one-year holding period as the reference horizon, thus with $N = 1$. This choice is consistent in cases where the product has a short duration or when a conservative short-term estimate is desired, while also allowing for potential future extensions over multi-year horizons (e.g., 3 years, as provided in certain KIDs).

From a statistical perspective, in addition to the mean and standard deviation, the third and fourth central moments (skewness and kurtosis) were also calculated, which are necessary to adjust the normal approximation of the distributions. The method employed was the Cornish-Fisher expansion, which allows the correction of the theoretical quantiles of the standard normal distribution by taking into account the asymmetry and flattening of the empirical distribution of returns.

The quality of the results, particularly for funds with distorted trends (such as GL, LA, and PE), highlights the importance of using the Cornish-Fisher correction to avoid underestimating the risk in cases where the distribution of returns significantly deviates from normality.

Finally, the VaR value was converted into equivalent volatility and used to determine the MRM risk class according to the thresholds established by the regulation (from 1 to 7, increasing according to the level of volatility).