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Research Article

Evaluating the Risk-Return Profile of a Portfolio of ESG and Traditional Assets Using a Hybrid Optimisation Model

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Abstract. This article examines the risk-return dynamics of portfolios combining environmental, social, and governance (ESG) assets with traditional investment instruments. A hybrid optimisation framework is applied, uniting mean-variance principles with combinatorial selection and machine learning techniques. The study addresses two central questions: whether ESG funds provide diversification benefits, and whether they mitigate downside risk in periods of financial stress. The analysis draws on a dataset of five ESG and five non-ESG funds, spanning varied sectors and risk profiles, observed over a five-year horizon marked by diverse macroeconomic conditions. Portfolio performance is evaluated using the Sharpe ratio, with differential evolution and support vector machine algorithms employed to capture linear and non-linear aspects of risk-adjusted returns. The findings reveal a consistent positive association between ESG allocation and portfolio performance. Optimised portfolios frequently allocated 80-90 per cent of their weight to ESG assets, particularly GRID and ESGV. ESG holdings were shown to strengthen diversification, improve upside potential, and reduce downside exposure, especially during volatile market phases. Traditional assets contributed stability but played a weaker role in enhancing risk-adjusted returns. Statistical analysis confirmed both research hypotheses: portfolios integrating ESG investments achieved higher Sharpe ratios without excessive risk, and ESG funds demonstrated resilience under adverse conditions. Machine learning models further underscored the significance of non-linear patterns, which enhanced the explanatory power of ESG exposure in the optimisation process. In sum, the study contributes to growing evidence that ESG assets not only advance sustainability objectives but also deliver measurable financial benefits. The hybrid methodological approach illustrates the importance of balanced allocation constraints and robust optimisation in portfolio design. These results suggest that incorporating ESG assets can simultaneously reinforce financial stability and support long-term sustainable development.

Keywords: portfolio rebalancing; sustainable investment; risk-adjusted returns; ESG and Non-ESG assets allocation; shape ratio; support vector machine algorithms.

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1. Introduction

The field of sustainable finance and sustainable investment has a history going back several decades. Research on sustainable finance has become a focus of interest in the last 15 years. According to Chitimea et al. [1], it pays to invest in sustainable investments if we think in a long-term scenario. The payback may take longer, but the effects are beneficial for both private and public organisations. According to the OECD, sustainable investment is a very broad concept that is closely linked to other investment approaches such as SRI - socially responsible investment, ESG (Investment in Association with Environmental, Social and Governance Investing), sustainable long-term investment or similar concepts [2].

Sustainable investment is important for financing sustainable development. Few investors, however, completely ignore financial returns and risk-taking when making their investments. Studies opposing sustainable investment argue that these approaches lead to more limited portfolios due to the narrower range of investment opportunities available compared to traditional capital markets [3]. At the same time, some studies highlight potential advantages: based on research by Yue et al. [4] conducted between 2014 and 2018, sustainable funds are less risky than traditional funds, at least in terms of market risk. In our study, we examine the risk and return characteristics of sustainable investment portfolios, and our results can be compared with the findings of previous research. In addition, we analyse the risk-return profile of sustainable investments when combined in a portfolio with traditional forms of investment. In doing so, we can demonstrate that sustainable investments are also worth including in the portfolios of investors who are less committed to sustainability, thereby broadening the investor base and increasing the attractiveness of such portfolios. In this way, we can contribute to mobilizing additional financing to achieve sustainable development. Based on our research objectives, we formulate the following hypotheses:

1) Diversification Benefit Hypothesis: Including ESG funds in the portfolio provides diversification benefits by reducing overall portfolio risk without reducing returns.

2) Downside Risk Hypothesis: ESG funds exhibit lower downside risk during market downturns compared to traditional funds, as ESG factors are linked to resilience during economic or environmental crises.

2. Literature Review

2.1. The Concept of Sustainable Investment Funds and the Findings of Previous Research on Their Performance

The intersection between financial markets and environmental, social, and governance (ESG) issues has become increasingly prominent in recent years, reflecting a growing recognition of the interconnectedness between sustainable practices and investment outcomes [5]. Monetary flows towards so-called sustainable investment funds are projected to grow to one third of the global market by 2025 (USD 53 trillion) [6]. A Sustainable Investment Fund is a financing instrument that mobilises capital for projects and companies focusing on mitigating climate change, preserving the environment, and promoting sustainable development. These funds provide financial support to initiatives that meet ESG criteria while at the same time generating competitive financial returns [7].

Over the past few decades, sustainable investment funds have evolved significantly in response to growing environmental concerns and the increasing need for sustainable finance. They are positioned within the well-known investment triangle of profitability, safety, and liquidity, but also pursue sustainability as an additional goal, with environmental sustainability typically at the forefront. Nevertheless, social and economic sustainability aspects can also be incorporated. In this sense, sustainable funds are generally understood as investment vehicles that invest in companies with a socially conscious or environmentally responsible approach [8]. In Belaid et al's [9] formulation, a sustainable investment fund (GIF) is an investment vehicle or financial instrument that focuses specifically on environmentally friendly projects and companies that promote sustainable development. According to Agoraki et al. [10], sustainable investment funds facilitate the transition towards lower carbon and climate resilient economies and are often characterised by strong resilience and lower return volatility compared to traditional instruments, especially in times of market turbulence.

Empirical research has examined their broader economic and corporate impacts. For instance, Chi et al. [11] showed that sustainable funds contribute to stock returns, reduce equity risk, and enhance social valuation by fostering corporate sustainable innovation and resource efficiency. At the same time, portfolio construction raises specific challenges. According to Alessandrini and Jondeau [12], there are two main challenges in building an ESG portfolio. First, improving the ESG quality of the portfolio should not come at the expense of lower financial performance. Second, it should not involve exposure to undesirable risk factors. Using an optimisation programme, they demonstrated that these two goals can be achieved together.

ESG funds have experienced rapid growth and demonstrated resilience during crises. For example, during the market turmoil of March 2020, ESG funds maintained positive cash flows, unlike their non-ESG counterparts, and proved less sensitive to short-term return fluctuations, reflecting a longer-term investment horizon and expectations of superior risk-adjusted performance [13]. Similarly, Arfaoui et al. [14] showed that sustainable funds offer diversification benefits against climate risks, providing insights for investors and policy makers to develop proactive strategies consistent with sustainability goals. While Yousaf et al. [15] found that the inclusion of sustainable bonds in equity portfolios during the COVID-19 pandemic generated the highest risk-adjusted returns compared to portfolios with other alternative assets in the sample. Their findings emphasise that sustainable investments enhance both financial stability and performance, particularly in turbulent markets.

Chang et al. [16] in their studies compared the financial performance of sustainable and conventional mutual funds in the US. In total, 131 sustainable mutual funds were compared with the average of all conventional mutual funds in their respective Morningstar categories. Among other things, they examined annual rates of return and Sharpe ratios. The results showed that sustainable mutual funds had lower returns and similar risks than traditional mutual funds in the corresponding Morningstar categories. Sustainable mutual funds underperformed on a risk-adjusted basis. This finding is consistent with the earlier finding of Kurtz and Dibartolomeo [17]. Research by Silva and Cortez [18] also supports the finding that sustainable funds tend to underperform the benchmark, especially European funds. This position is supported by Renneboog et al. [19], who find that ESG funds registered in France, Japan and Sweden underperform compared to traditional ones. The underperformance of funds is mainly concentrated in periods when short-term interest rates are lower than normal and in non-crisis periods.

A contrasting finding was made by Guimaraes et al. [20], who examined a dataset of 3840 equity mutual funds between 2006 and 2020 and found that ESG-related funds achieved on average higher risk-adjusted returns during periods of financial austerity. These results suggest that during market downturns, investors can achieve better risk-adjusted returns by investing in sustainable funds. Similar results were observed for the COVID-19 period, suggesting that ESG-related funds also outperformed 'traditional' funds during the pandemic. However, the evidence remains mixed. While Guimaraes et al. [20], highlight the resilience of ESG funds in times of crisis, Bauer et al. [21] show that performance can also vary significantly across countries. They found that US ethical funds underperformed conventional funds, although UK funds outperformed and German funds showed no significant differences.

Becchetti et al. [22] examined the performance of socially responsible funds and conventional funds in different market (geographic area and class size) segments over the period 1992-2012. A key finding of their analysis is that during the 2007 global financial crisis, socially responsible funds played an "insurance role", outperforming conventional funds. Gao et al. [23] do not demonstrate significant differences in risk-adjusted returns between ESG and conventional funds. They conclude that the relationship between ESG and return/risk profile is overwhelmingly neutral or even positive. While these studies focus on empirical outcomes, Pedersen et al. [24] offered a theoretical framework to address the portfolio dilemma by introducing the concept of the ESG-efficient frontier, which identifies the maximum achievable Sharpe ratio for each ESG level. Using an ESG-adjusted capital asset pricing model, they argued that fund managers can determine equilibrium asset values while accounting for sustainability factors.

Based on the literature review, it can be concluded that there is no clear view on the performance of ESG funds and further quantitative analysis is worthwhile. Combining ESG and traditional funds in a portfolio and evaluating risk and return profiles using modern tools could provide new research results in addition to comparing with the results of previous research.

2.2. Sharpe ratio

The performance of portfolios is evaluated using the Sharpe ratio. The use of the risk-return ratio to rank risky investments dates back more than 70 years to Roy [25]. It was then first used by Sharpe [26] to evaluate portfolios (investment funds) and has become one of the most popular indicators in the world of academics and practitioners alike, under the name of the Sharpe index [27].

The Sharpe ratio can be easily applied to any return series without the need for additional information on the source of volatility and/or profitability. It is commonly used to compare the risk-adjusted returns of different types of investments such as equities, ETFs, mutual funds and investment portfolios. It is based on Markowitz's mean-variance paradigm, which assumes that the mean and standard deviation of the distribution of one-period returns are sufficient statistics to evaluate the prospects of an investment portfolio [28].

The ratio is calculated as follows:

$$\text{Sharpe ratio} = \frac{r_i - r_f}{\sigma(r_i)} \quad (1)$$

where r_i is the return of instrument; r_f is the risk-free rate of return; and $\sigma(r_i)$ is the standard deviation of return of instrument i.

Since the standard deviation of the portfolio return is a measure of the risk of the portfolio, the Sharpe ratio is an indicator of the risk-adjusted return. If its value is positive, then the portfolio has been able to generate a return in excess of the risk assumed. The Sharpe ratio can therefore indicate whether the higher return achieved by a portfolio was due to good investment decisions or simply the result of a riskier investment strategy.

3. The Processed Data and the Research Methodology

This analysis presents five ESG funds alongside five non-ESG funds for comparison. The iShares Global Clean Energy ETF (ICLN) tracks the S&P Global Clean Energy Index and invests in clean energy companies like Enphase Energy, while the Vanguard ESG U.S. Stock ETF (ESGV) provides broad exposure to U.S. stocks with a focus on companies that meet environmental, social, and governance criteria. The First Trust Global Wind Energy ETF (FAN) focuses on wind energy, and the First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN) and First Trust NASDAQ Clean Energy Smart Grid Infrastructure Index offer moderate to high-risk exposure to clean energy and smart grid technology. In contrast, non-ESG assets include the SPDR S&P 500 ETF Trust (SPY) and Vanguard Total Stock Market ETF (VTI), both with moderate risk profiles and diversified holdings. Higher-risk assets like the ARK Innovation ETF (ARKK) and Fidelity Small Cap Growth Fund (FCPGX) focus on disruptive innovation and small-cap growth, while the American Funds Growth Fund of America (AGTHX) seeks long-term capital appreciation.

To perform a comprehensive analysis of the characteristics of each asset with the aim of capturing the potential impact of green assets, we selected a 5-year period from September 3, 2019, to August 30, 2024. This timeframe covers a diverse array of macroeconomic conditions, including phases of economic growth, recession, market volatility, and varying interest rate environments. When selecting ESG assets, we focused on high market capitalisation companies and sectors with significant growth potential, particularly in light of the increasing global emphasis on sustainability and renewable energy. To ensure a well-rounded analysis, we also included non-ESG assets that matched similar market capitalisation and risk profiles and involved diverse sectors. The main characteristics of the instruments included in the study are presented in Table 1 and Table 2. The research is based on the officially published adjusted closing prices of the analysed assets, derived from historical data available on *Investing.com*.

Table 1. Overview of ESG Funds Included in the Analysis.

Asset	Objective	Top Holdings	Geographic Exposure	Sectors	Risk Level
iShares Global Clean Energy ETF (ICLN)	Tracks the S&P Global Clean Energy Index, focusing on companies involved in clean energy production.	Enphase Energy, Vestas Wind Systems, Orsted	Global (U.S. & Europe)	Utilities, Energy	Moderately high-risk
Vanguard ESG U.S. Stock ETF (ESGV)	Tracks the FTSE U.S. All Cap Choice Index, providing exposure to U.S. stocks that meet certain environmental, social, and governance (ESG) criteria.	Apple, Microsoft, Alphabet	Primarily U.S.	Diversified across all sectors, excluding companies involved in activities not aligning with ESG criteria	Moderate risk
First Trust Global Wind Energy ETF (FAN)	Tracks the ISE Clean Edge Global Wind Energy Index, focusing on the wind energy industry.	Siemens Gamesa, Vestas Wind Systems, Orsted	Global (Europe & U.S.)	Industrial, Utilities	High-risk, sensitive to regulatory changes
First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN)	Tracks the NASDAQ Clean Edge Green Energy Index, focusing on companies in clean energy.	Tesla, Enphase Energy, Sunrun	Primarily U.S.	Consumer Discretionary, Energy	Moderate to high-risk
First Trust NASDAQ Clean Energy Smart Grid Infrastructure Index (GRID)	Focuses on companies involved in clean energy and smart grid technology.	Itron, Siemens, ABB	Global	Utilities, Information Technology	Moderate risk, potential growth in smart tech

Source: Own editing based on [29].

Table 2. Overview of Non-ESG Funds Included in the Analysis.

Asset	Objective	Top Holdings	Geographic Exposure	Sectors	Risk Level
SPDR S&P 500 ETF Trust (SPY)	Tracks the S&P 500 Index, providing exposure to 500 of the largest U.S. companies.	Apple, Microsoft, Amazon	Primarily U.S.	Diversified across all sectors	Moderate risk

Vanguard Total Stock Market ETF (VTI)	Seeks to track the performance of the CRSP US Total Market Index, representing the entire U.S. stock market.	Apple, Microsoft, Tesla	Primarily U.S.	Diversified across all sectors	Moderate risk
ARK Innovation ETF (ARKK)	Focuses on disruptive innovation across sectors, including genomics, automation, and fintech.	Tesla, Roku, CRISPR	Primarily U.S.	Technology, Health Care	High risk (due to growth and innovation focus)
Fidelity Small Cap Growth Fund (FCPGX)	Invests in small-cap growth companies that are expected to grow faster than the overall market.	Etsy, Chegg, Five9	Primarily U.S.	Technology, Consumer Discretionary	High risk (due to small-cap focus)
American Funds Growth Fund of America (AGTHX)	Seeks long-term growth of capital by investing in companies with the potential for above-average growth.	Microsoft, Visa, Facebook	Primarily U.S.	Technology, Consumer Discretionary	Moderate risk

Source: Own editing based on [29].

To construct a portfolio of five assets from a pool of ten options, we developed a model based on the mean-variance optimisation approach. This model enables the selection of the most efficient combinations of assets using historical price data. The model calculates simple returns, expected mean returns, and the covariance matrix of returns. It defines an objective function to maximize the Sharpe ratio using differential evolution optimisation, constraining the weights of selected assets between specified minimum and maximum values. The algorithm evaluates all possible combinations of five assets, identifies the optimal weights that yield the highest Sharpe ratio, and outputs the best combinations of assets along with their corresponding weights and the maximum Sharpe ratio achieved. The binomial coefficient can be used to calculate the total number of combinations that the programme loops through.

$$\binom{n}{k} = \frac{n!}{k!(n-k)!} \tag{2}$$

where n = the total number of available assets, k = the number of assets selected for the portfolio

$$\binom{10}{5} = \frac{10!}{5!(10-5)!} = \frac{10\times9\times8\times7\times6}{5\times4\times3\times2\times1} = 252 \tag{3}$$

The 252 combinations consist of 1,000 iterations each, resulting in a total of 252,000 iterations, which underscores the robustness of our quantitative model. As the risk-free rate, we applied 1.466%, based on the US 10-year bond yield on September 3, 2019. To ensure balanced portfolio weights, we constrain asset allocations to range between 5% and 80%, preventing extreme weights that could increase portfolio risk or result in asset exclusion. After running the model, we identify the optimal weights that yield the highest Sharpe ratio and output the best combinations of assets, their corresponding weights, and the maximum Sharpe ratio achieved. Average return and standard deviation were annualized using the 252 trading days approach. The programme was developed in RStudio, primarily utilising the DEoptim package, which implements the Differential Evolution optimisation algorithm suitable for solving complex, nonlinear problems. By implementing weight limits while simultaneously enforcing the selection of combinations, we ensure that the model evaluates each possible combination without bias from outliers. This is particularly important as we plan to compile optimal portfolios from assets that are grouped into specific categories. We employed the mean-variance method as follows:

1. Expected Portfolio Return

$$E(\mathrm{R_p}) = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{w_i} \cdot \mathrm{E(R_i)} \tag{4}$$

where: $E(R_p)$ = expected return of the portfolio, $\mathrm{w_i}$= weight of asset i in the portfolio, $\mathrm{E(R_i)}$ = expected return of asset i, n = total number of assets in the portfolio.

2. Portfolio Variance

$$\sigma_{\mathrm{p}}^2 = \sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{w_i^2} \cdot \sigma_{\mathrm{i}}^2 + \sum_{\mathrm{i=1}}^{\mathrm{n}} \sum_{\mathrm{j \neq i}} \mathrm{w_i} \cdot \mathrm{w_j} \cdot \sigma_{\mathrm{ij}} \tag{5}$$

where: σ_{p}^2 = variance of the portfolio, σ_{i}^2 = variance of asset i, σ_{ij} = covariance between assets i and j.

3. Standard Deviation of Portfolio

$$\sigma_{\mathrm{p}} = \sqrt{\sigma_{\mathrm{p}}^2} \tag{6}$$

4. Sharpe Ratio

$$\mathrm{S} = \frac{\mathrm{E(R_p) - R_f}}{\sigma_{\mathrm{p}}} \tag{7}$$

where: $\mathrm{E(R_p)}$ = expected return of the portfolio, $\mathrm{R_f}$ = risk-free rate, σ_{p} = standard deviation of the portfolio.

The logic of the model is straightforward yet robust. If we observe that a higher overall weight of ESG assets is associated with an increased Sharpe ratio - assuming this relationship is statistically significant - we can accept the hypothesis that ESG assets improve portfolio diversification and enhance returns. This would suggest that ESG investments contribute not only to maximizing returns but also to reducing risk through diversification. However, if this hypothesis is confirmed, further investigation into downside risk is warranted, as ESG funds may help mitigate downside risk, but this effect is not guaranteed. On the other hand, if the model predominantly selects non-ESG assets, we can reject both the diversification benefit and the downside risk hypotheses, indicating that ESG criteria may not enhance performance or provide meaningful diversification benefits in this context.

This modelling logic is illustrated in Figure 1, which outlines the full algorithmic process flow.

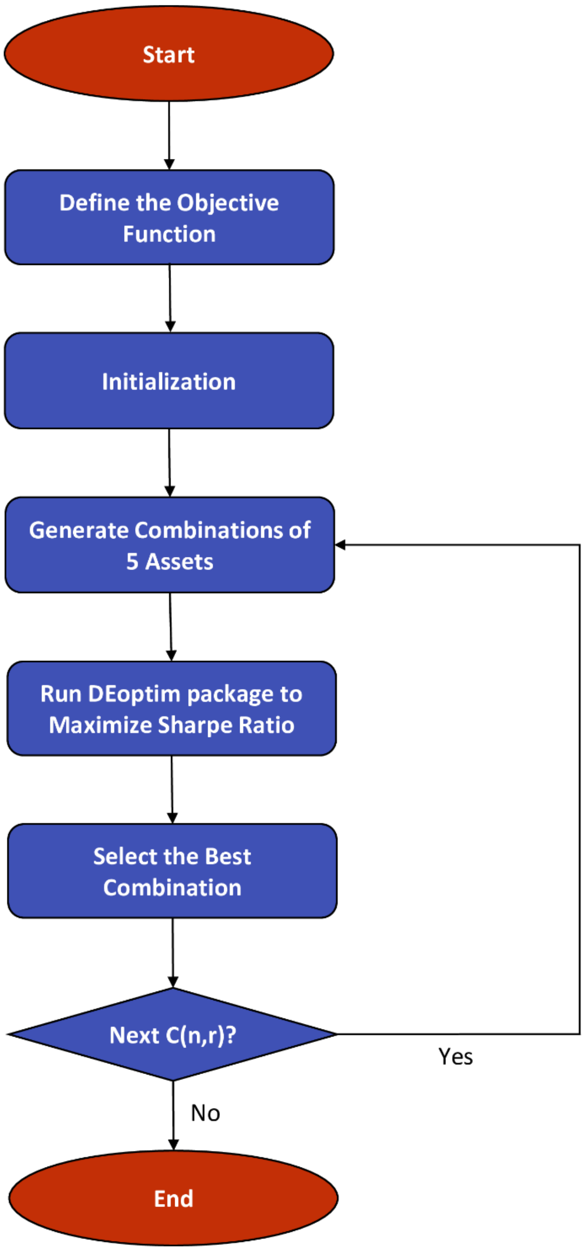

Figure 1. Process Flow of the Algorithm.
Source: Own editing.

To examine the downside risk hypothesis, we calculate downside risk by considering only the negative standard deviation. This measure is subtracted from the overall risk (standard deviation) to determine upside risk (positive risk), which is then adjusted based on the respective asset weights. This approach allows us to separately assess the effect of upside risk for both ESG and non-ESG assets within the portfolio. If the first hypothesis is supported, we might expect ESG upside risk to be positively correlated with the portfolio's Sharpe ratio, while non-ESG upside risk will be negatively correlated with it. Higher upside risk indicates that the asset is more likely to achieve returns above its expected performance, suggesting a greater potential for gains during favorable market conditions. Downside risk only focuses on potential losses, neglecting upside opportunities, while asset weight-adjusted upside risk provides a more balanced view, capturing both potential returns and risks. This reverse approach offers a more nuanced risk-return analysis, better aligning with investment goals focused on both risk mitigation and capital appreciation. This analysis will be applied to the optimal combination of assets identified by the previously introduced programme, enabling us to focus on the best risk-adjusted portfolios and the underlying dynamics of diversification.

$$\text{Portfolio Upside Risk} = \sum_{i=1}^{n} \left((\sigma_i - \sigma_{D,i}) \times w_i \right) \tag{8}$$

where: n = total number of assets in the portfolio (both ESG and Non-ESG), σ_i = standard deviation of asset i, $\sigma_{D,i}$ = downside risk of asset i, w_i = weight of asset i in the portfolio

This hybrid portfolio optimisation method integrates combinatorial asset selection with strict minimum and maximum allocation constraints within a mean-variance framework, making it more suitable for real-life scenarios. Unlike traditional mean-variance optimisation, which can lead to extreme asset weights and create portfolios that are mathematically optimised but riskier from a risk management perspective - due to excessive exposure to underlying holdings and sectors - this approach allows for the selection of 5 assets from a pool of 10, where each asset has a 50% chance of being included, ensuring an equal opportunity for both ESG and non-ESG assets to be represented without being zeroed out based on covariance-based selection, given the weight limits. This adds a layer of flexibility to incorporate specific ESG assets while maintaining a balanced representation. By enforcing weight limits and preventing "over-concentration" or "zeroing out" of any asset in the selected combinations, the method ensures more stable and diversified portfolios. This results in a balanced assessment of how ESG and non-ESG assets contribute to the overall risk-return profile, facilitating informed and practical decision-making regarding the inclusion of ESG characteristics while maintaining a comprehensive risk management approach.

4. Results

4.1. Descriptive Statistics

In this section, we will present a descriptive analysis of the assets analysed in the quantitative model.

Table 3. Descriptive Statistics of Simple Returns.

	Average Return	Standard Deviation	Skewness	Kurtosis
ICLN	10.75%	32.79%	-0.1444	4.8022
ESGV	15.93%	21.97%	-0.4471	10.0522
FAN	8.44%	24.57%	-0.3027	7.8952
QCLN	19.25%	41.77%	-0.0016	2.1874
GRID	22.30%	25.63%	-0.6545	10.3156
SPY	15.48%	20.95%	-0.5549	11.6603
VTI	14.97%	21.46%	-0.557	12.0243
ARKK	11.90%	47.28%	-0.0438	1.8083
FCPGX	14.16%	25.88%	-0.6948	6.1385
AGTHX	17.34%	22.68%	-0.6329	6.9286

Source: Own editing.

The performance analysis of the selected assets reveals notable differences between ESG-related and non-ESG assets, particularly in terms of average return, standard deviation, skewness, and kurtosis. The results are shown in Table 3. For the ESG assets, average returns range from 8.44% for FAN to 22.30% for GRID, with ESGV offering a solid return of 15.93%. These returns indicate a robust performance; however, the associated risks are also significant, as seen in the high standard deviations, especially for QCLN (41.77%) and GRID (25.63%). This suggests that while ESG investments can yield higher returns, they come with increased volatility and risk. In contrast, the non-ESG assets exhibit generally lower average returns, ranging from 11.90% for ARKK to 17.34% for AGTHX, with SPY and VTI performing around 15%. The standard deviations for these assets are also lower, indicating less volatility in their returns compared to the ESG group. This makes non-ESG investments potentially more appealing for risk-averse investors who prioritize stability over higher returns. The period under analysis includes several market shocks, and the average returns of ESG assets align with the findings of Silva and Cortez [18], which suggest that ESG investments tend to perform better during periods of crisis.

Analysing the skewness of the return distributions reveals a consistent pattern for both groups, as all assets exhibit negative skewness. This indicates a longer left tail and a higher likelihood of extreme negative returns. GRID shows the most pronounced case among ESG funds, while SPY and VTI display similar risks in the non-ESG group. Overall, the presence of negative skewness across both categories suggests that the risk of significant losses is a common trait, regardless of investment strategy.

Kurtosis measures, which indicate the tailedness of return distributions, provide additional insights into the risk profiles of these assets. ESG assets like ESGV (kurtosis of 10.0522) and GRID (10.3156) exhibit higher kurtosis values, suggesting an increased likelihood of extreme returns. In comparison, the non-ESG assets, particularly SPY and VTI, display even higher kurtosis (11.6603 and 12.0243, respectively), indicating a potential for significant outlier events. As previously noted, it is crucial to recognise that the portfolio-level performance of a given asset can contradict the expected characteristics based on descriptive statistics. For instance, an asset with high kurtosis may not always lead to extreme outcomes when it is part of a diversified portfolio, and this might be the case for ESG assets as well.

In conclusion, while the ESG assets examined may offer higher potential returns, they also come with increased volatility and risks of extreme outcomes, due to sensitivity to regulatory changes and the uncertain impacts of innovations such as smart technology. In contrast, the non-ESG assets analysed tend to provide steadier performance, making them more appealing to risk-averse investors. Notably, the statistical analysis indicates that the ESG assets exhibit higher kurtosis, suggesting a greater likelihood of extreme returns, which could impact overall portfolio stability. Additionally, the descriptive statistics reveal that both groups contain assets with different risk-return profiles, enhancing the validity of further analysis. The critical question remains whether incorporating potentially riskier ESG funds can mitigate overall risk or enhance the risk-adjusted profile of a diversified portfolio, especially amid market fluctuations and changing economic conditions.

4.2. Correlation Matrix

After the descriptive statistics, we constructed a correlation matrix for the yield of assets for both periods (Table 4).

Table 3. Correlation Matrix of the Returns of the Instruments.

	ICLN	ESGV	FAN	QCLN	GRID	SPY	VTI	ARKK	FCPGX	AGTHX
ICLN	1									
ESGV	0.6971	1								
FAN	0.8533	0.7367	1							
QCLN	0.8936	0.7483	0.7312	1						
GRID	0.8053	0.8794	0.8080	0.8159	1					
SPY	0.6772	0.9919	0.7333	0.7129	0.8735	1				
VTI	0.7061	0.9930	0.7497	0.7480	0.8904	0.9941	1			
ARKK	0.6979	0.7585	0.6187	0.8186	0.6920	0.7012	0.7372	1		
FCPGX	0.7643	0.9017	0.7344	0.8307	0.8634	0.8722	0.9043	0.8393	1	
AGTHX	0.7131	0.9692	0.7238	0.7864	0.8566	0.9480	0.9567	0.8295	0.9140	1

Note: All p-values are less than 0.001.
Source: Own editing.

The correlation matrix shows strong relationships between the selected ESG and non-ESG assets. Within the ESG group, ICLN, ESGV, and FAN exhibit high correlations with each other (e.g., ICLN-FAN at 0.8533 and ESGV-FAN at 0.7367), suggesting that these assets tend to move together. Similarly, QCLN and GRID display substantial correlations with other ESG assets, particularly with ICLN (0.8936 and 0.8053, respectively), indicating that ESG investments in clean energy and infrastructure are likely influenced by common market factors, such as regulatory changes and innovations in renewable energy. When comparing ESG assets with non-ESG assets, correlations remain significant but slightly lower. For example, ICLN shows moderate correlations with SPY (0.6772) and VTI (0.7061), while ESGV's correlations with SPY (0.9919) and VTI (0.9930) are remarkably high. This suggests that while ESG assets are aligned with broader market movements, their performance also diverges based on sector-specific dynamics, such as clean energy versus large-cap technology. Further analysis shows that non-ESG assets such as FCPGX and AGTHX also have strong correlations with ESG funds, largely due to overlapping exposure to technology and consumer discretionary sectors. This shared reliance on major tech stocks highlights common performance drivers across both ESG and non-ESG portfolios.

The generally high correlation between non-ESG assets, particularly SPY and VTI (0.9941), reflects their broad exposure to the U.S. market and similar sector diversification. Both ETFs track large-cap U.S. companies and maintain significant holdings in technology (e.g., Apple, Microsoft, Amazon), sectors that are common across both ESG and non-ESG portfolios. While non-ESG funds may appear more stable due to lower volatility, they still share performance trends with ESG assets, particularly when large-cap technology stocks dominate the holdings. This interconnectedness underscores how both ESG and non-ESG assets are influenced by broader market movements, especially in sectors driven by innovation and regulatory factors, making the inclusion of both types of funds in a diversified portfolio relevant for investors seeking balanced exposure to growth and sustainability themes. Despite these correlations, the difference in risk-return profiles within each group suggests that further analysis of portfolio-level diversification benefits is necessary to determine how well these assets complement each other in terms of risk mitigation and return optimisation.

4.3. Portfolio optimalization

In this section, we will present the results of the portfolio optimisation process conducted by our algorithm. The analysis focuses on optimising the risk-return trade-off between ESG and non-ESG assets.

The results of our optimisation model reveal a strong correlation between the portfolio's ESG asset weight and the Sharpe ratio. A correlation coefficient of 0.7607 underscores this robust relationship, with statistical significance ($p < 0.001$) across the top 252 combinations ranked by the algorithm. Additionally, the R^2 value of 0.5787 indicates that over half of the variance in the Sharpe ratio is explained by the portfolio's ESG asset weight, suggesting a good fit for the model. This underscores the substantial impact of ESG asset allocation on optimising risk-adjusted returns as observed by Kumar et al. [30] Notably, in the top ten scenarios generated by the algorithm, ESG assets represent 80-90% of the total portfolio weight, with ESGV and GRID emerging as dominant assets, further emphasizing the outsized influence of ESG exposure on portfolio performance.

In addition to least squares linear regression, we employed Support Vector Machine (SVM) algorithm, a supervised machine learning method, to analyse the relationship between Sharpe Ratio and ESG weight. This method offers a more flexible approach compared to traditional linear models by allowing for non-linear relationships through different kernel functions. In addition to the linear kernel, we chose polynomial and radial kernels to capture complex patterns in the data and enhance the model's ability to account for intricate interactions between the two variables. The default parameter values used in the SVM models were as follows: C = 1 (the regularization parameter), gamma = 1 / number of features (for the radial kernel), epsilon = 0.1 (the tolerance of the stopping criterion), and cost = 1 (same as C, for regularization).

This relationship is visualised in Figure 2, which plots the ESG weight against the Sharpe ratio using least squares linear regression.

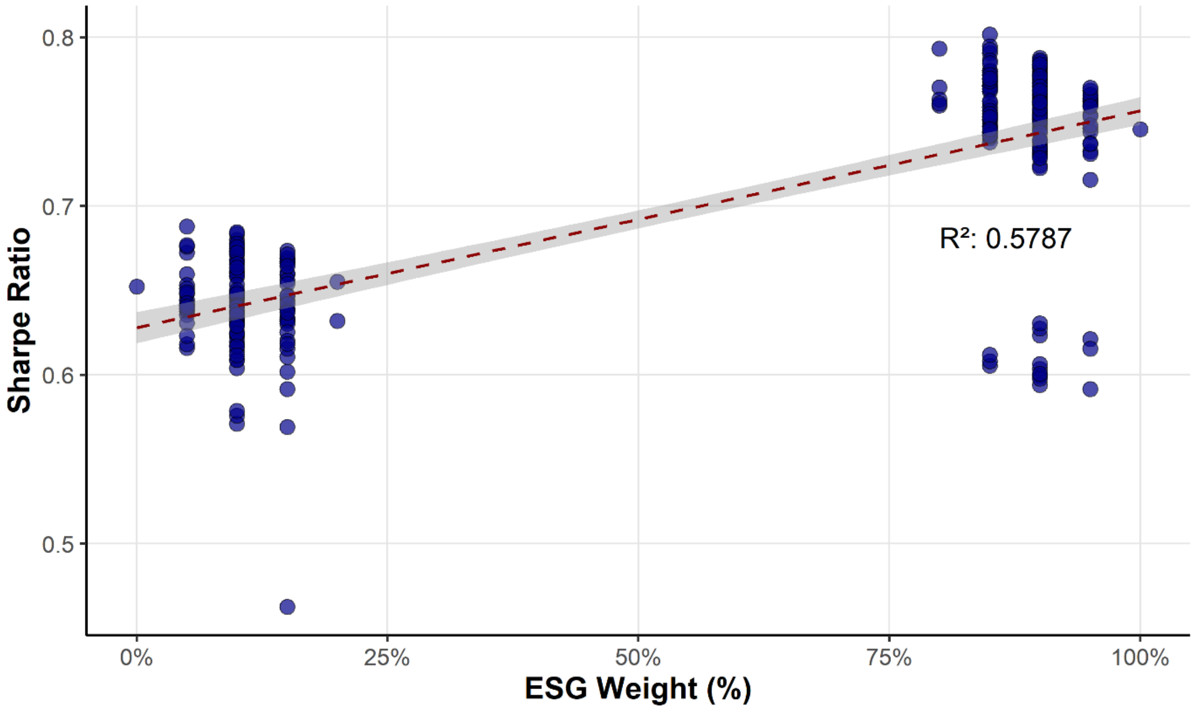

Figure 2. Relationship between Portfolio Sharpe Ratio and ESG Weight using Least Squares Linear. Regression.
Source: Own editing.

Table 4. Performance Metrics of SVM Models with Different Kernels for Sharpe Ratio vs ESG Weight.

Kernel	R^2	MSE	RMSE	MAE	RSS	Support Vectors
Linear	0.5566	0.0019	0.0440	0.0263	0.4870	186
Polynomial	0.4994	0.0022	0.0467	0.0303	0.5499	205
Radial	0.5807	0.0018	0.0427	0.0249	0.4605	196

Source: Own editing.

Table 5 presents the performance metrics of the SVM models using different kernels for predicting the Sharpe Ratio based on ESG weight.

The linear kernel, which assumes a direct linear relationship between ESG weight and Sharpe ratio, achieved an R^2 of 0.5566, indicating that approximately 55.66% of the variance in Sharpe ratio is explained by ESG weight. The Mean Squared Error (MSE) was 0.0019, translating to a Root Mean Squared Error (RMSE) of 0.044, showing a relatively small average error in predictions. The Mean Absolute Error (MAE) was 0.0263, suggesting that the average magnitude of prediction errors was low. With a Residual Sum of Squares (RSS) of 0.4870 and 186 support vectors, the linear kernel demonstrated competitive performance, particularly for simpler relationships, although it may lack the flexibility to capture more complex patterns, as seen in Figure 3.

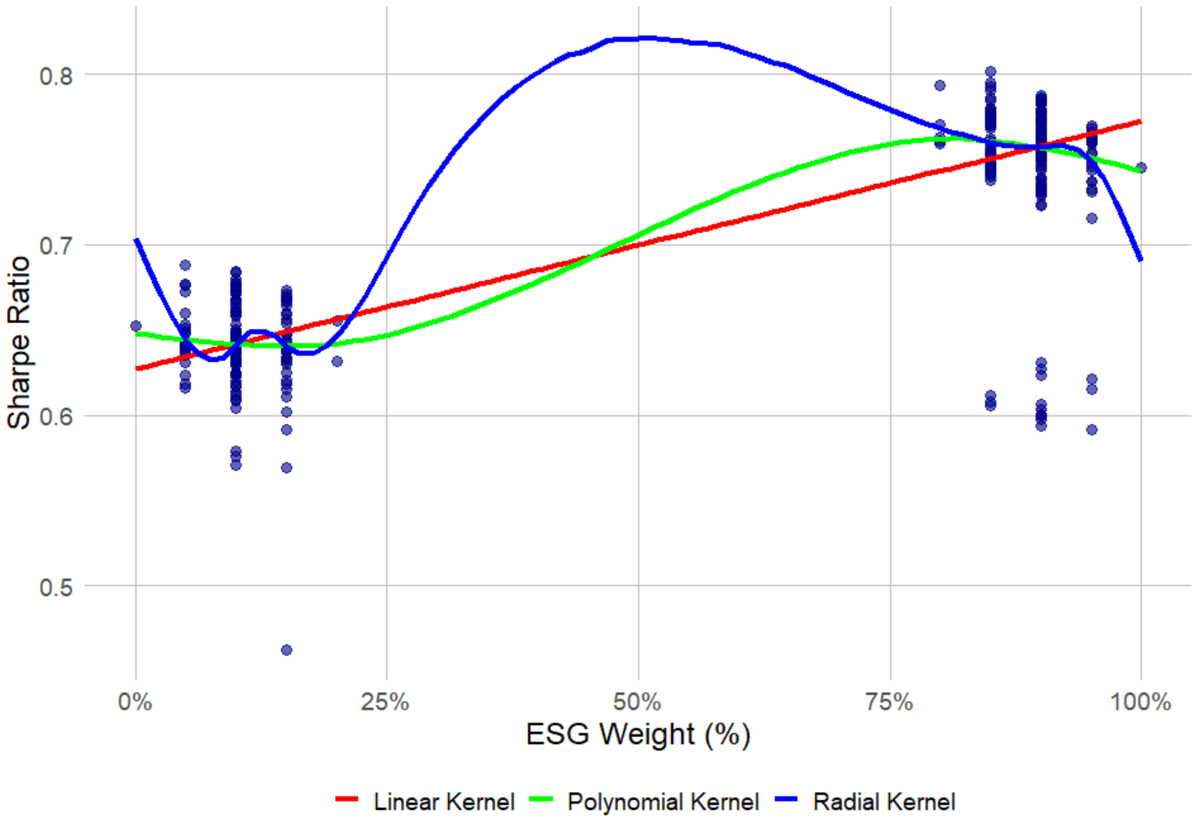

Figure 3. Impact of ESG Weight on Sharpe Ratio Across SVM Kernels.
Source: Own editing.

The polynomial kernel was less effective in modelling the relationship, explaining only about half of the variance and generating higher prediction errors compared to the other approaches. While it is theoretically capable of capturing complex, non-linear interactions, in this case the added complexity did not translate into better predictive performance. Instead, the results suggest potential overfitting or suboptimal parameterization, which limits the polynomial kernel's suitability relative to the more consistent linear model and the superior accuracy of the radial kernel.

The radial kernel, which excels at capturing highly non-linear relationships, achieved the best performance among the kernels. It had the highest R^2 of 0.5807, explaining 58.07% of the variance in Sharpe Ratio. The MSE was the lowest at 0.0018, corresponding to an RMSE of 0.0427, indicating the most accurate predictions. Additionally, the MAE was the smallest at 0.0249, reflecting the lowest average error. The RSS was the lowest at 0.4605, demonstrating the kernel's superior fit to the data. With 196 support vectors, the radial kernel struck an effective balance between model complexity and predictive accuracy, making it the most suitable choice for capturing complex relationships in this dataset.

The analysis of SVM kernels highlights varying levels of effectiveness in capturing the relationship between ESG weight and Sharpe ratio. The linear kernel performed comparably to the least squares linear regression, achieving an R^2 of 0.5566 versus 0.5787 from the linear correlation, suggesting strong alignment with linear patterns in the data. However, the radial kernel outperformed all methods with an R^2 of 0.5807, the lowest MSE (0.0018), and the smallest MAE (0.0249), indicating superior accuracy and flexibility in capturing non-linear relationships. In contrast, the polynomial kernel, despite its ability to model complex patterns, underperformed with an R^2 of 0.4994, higher errors, and potential overfitting. These results suggest that while there is a significant linear component, the relationship between ESG weight and Sharpe ratio is not fully linear, as evidenced by the radial kernel's superior performance.

Table 5. Top Ten Portfolios Compiled by the Algorithm with Overall ESG Asset Weight.

Rank	Asset 1	Asset 2	Asset 3	Asset 4	Asset 5	ESG weight	Sharpe ratio
1	ESGV	GRID	SPY	VTI	AGTHX	85.00%	0.8017
2	ESGV	GRID	SPY	FCPGX	AGTHX	85.00%	0.7948
3	GRID	SPY	VTI	FCPGX	AGTHX	80.00%	0.7933
4	ESGV	GRID	VTI	FCPGX	AGTHX	85.00%	0.7924
5	ESGV	GRID	SPY	VTI	FCPGX	85.00%	0.7906
6	ESGV	FAN	GRID	SPY	AGTHX	90.00%	0.7877
7	ESGV	QCLN	GRID	SPY	AGTHX	90.00%	0.7862
8	FAN	GRID	SPY	VTI	AGTHX	85.00%	0.7862
9	ESGV	FAN	GRID	VTI	AGTHX	90.00%	0.7854
10	QCLN	GRID	SPY	VTI	AGTHX	85.00%	0.7847

Source: Own editing.

Table 6 presents the top ten optimised portfolios and their respective ESG weights, which serve as the basis for the following allocation analysis.

The analysis of 252 optimised portfolios reveals that ESG assets account for 54.46% of the total average weight, indicating a near-equal distribution between ESG and Non-ESG assets. Within the ESG group, GRID leads with 40.00%, highlighting its dominance as a clean energy fund, followed by ESGV at 6.96%. Smaller contributions from ICLN (2.50%), FAN (2.50%), and QCLN (2.50%) suggest these funds attract less capital due to their specialized focus. Conversely, Non-ESG assets make up 45.54% of the total, with SPY holding the highest weight at 12.93% and AGTHX at 23.32%, reflecting ongoing confidence in traditional equity investments. Additionally, the presence of VTI (3.99%), FCPGX (2.50%), and ARKK (2.80%) indicates smaller allocations, likely influenced by market volatility. Overall, this distribution highlights a growing inclination towards sustainable investments while maintaining a balance with established non-ESG options, demonstrating investors' adaptive strategies amid evolving market trends, as concluded by Whelan et al. [31].

Figure 4 visualises this distribution, showing the relative weights of ESG and non-ESG assets across all optimised portfolios.

Figure 4. Distribution of Asset Weights across Optimised Portfolios.
Source: Own editing.

To evaluate the downside risk associated with ESG funds, we utilise the outputs generated by our optimisation algorithm. Specifically, we incorporate the downside risk measures previously highlighted and compute the weight-adjusted upside risk for each asset across the 252 optimised portfolios. This approach enables us to discern the proportion of upside risk attributable to both ESG and non-ESG assets. Our findings reveal a robust positive correlation of 0.7866 ($p < 0.001$) between ESG upside risk and the Sharpe ratio, indicating that the excess returns are predominantly driven by ESG assets. Conversely, we observe a strong negative correlation of -0.7744 ($p < 0.001$) between non-ESG upside risk and the Sharpe ratio, suggesting that non-ESG assets contribute less favorably to overall returns. This indicates a trend whereby additional returns are primarily derived from ESG investments, while non-ESG assets exhibit a detrimental effect on risk-adjusted performance. In line with the findings of Özkan et al. [32], our results further support the notion that ESG investments can act as hedges and diversifiers, contributing positively to risk-adjusted performance and enhancing overall returns.

Similarly to the analysis between the Sharpe ratio and ESG weight, we applied SVM kernels to analyse the connection between the Sharpe Ratio and ESG Upside Risk, aiming to verify the results observed with least squares linear regression. Given that risk measures can, in some cases, exhibit non-linear behaviour due to non-normal distributions of returns and rapid market movements, we may expect a non-linear relationship between these variables as well. This makes the use of SVM kernels particularly relevant, as they can effectively capture more complex interactions that linear models might not fully represent.

Table 6. Performance Metrics of SVM Models with Different Kernels for Sharpe Ratio vs ESG Upside Risk.

Kernel	R^2	MSE	RMSE	MAE	RSS	Support Vectors
Linear	0.6066	0.0017	0.0414	0.0262	0.4321	195
Polynomial	0.5409	0.0020	0.0447	0.0319	0.5043	210
Radial	0.6198	0.0017	0.0407	0.0245	0.4176	190

Source: Own editing.

Table 7 summarises the performance of SVM models with different kernels in capturing the relationship between Sharpe Ratio and ESG Upside Risk.

The results show that the linear kernel achieved an R^2 of 0.6066, explaining 60.66% of the variance in the relationship between the Sharpe ratio and ESG upside risk. It had a relatively low Root Mean Squared Error (RMSE) of 0.0414 and a Mean Absolute Error (MAE) of 0.0262, suggesting reasonable prediction accuracy. The polynomial kernel, while capturing more complex interactions, resulted in a lower R^2 of 0.5409, indicating it explained just 54.09% of the variance. It also had higher error values, with an RMSE of 0.0447 and an MAE of 0.0319, suggesting less accurate predictions. The radial kernel outperformed both, with the highest R^2 of 0.6198, explaining 61.98% of the variance. It also had the lowest RMSE of 0.0407 and MAE of 0.0245, indicating the best fit and most accurate predictions. The residual sum of squares (RSS) was the lowest for the radial kernel (0.4176), making it the most effective kernel for capturing the relationship between the Sharpe ratio and ESG upside risk.

Figure 5 visualises these results, showing the relationship between ESG upside risk and Sharpe ratio across different SVM kernels.

These findings confirm a robust positive correlation between ESG upside risk and the Sharpe ratio, indicating that excess returns are largely driven by ESG assets. Unlike the ESG weight analysis, where performance differences across kernels were more noticeable, the variance here is relatively small, with all three kernels producing broadly consistent results. Nevertheless, the radial kernel still achieves the best fit and accuracy, reinforcing the view that stronger ESG ratings are associated with lower downside risk and greater portfolio resilience.

The analysis of the best and worst asset combinations highlights the significant impact of upside risk on the Sharpe ratio. In the worst-case scenario, the portfolio heavily favors non-ESG assets like FCPGX and ARKK, which constitute 85% of the allocation. This concentration results in high overall risk (up to 47.28%) and substantial downside risk, particularly from ARKK, limiting the adjusted upside risk to only 0.7%. This unfavorable risk-return profile contributes to a low Sharpe ratio. Conversely, the best-case scenario features a predominance of ESG assets, particularly GRID (80%), leading to lower overall risk (up to 25.63%) and favorable downside risk levels. This strategic allocation enhances adjusted upside risk and significantly improves the Sharpe ratio, demonstrating that prioritizing ESG investments can optimise risk-adjusted returns.

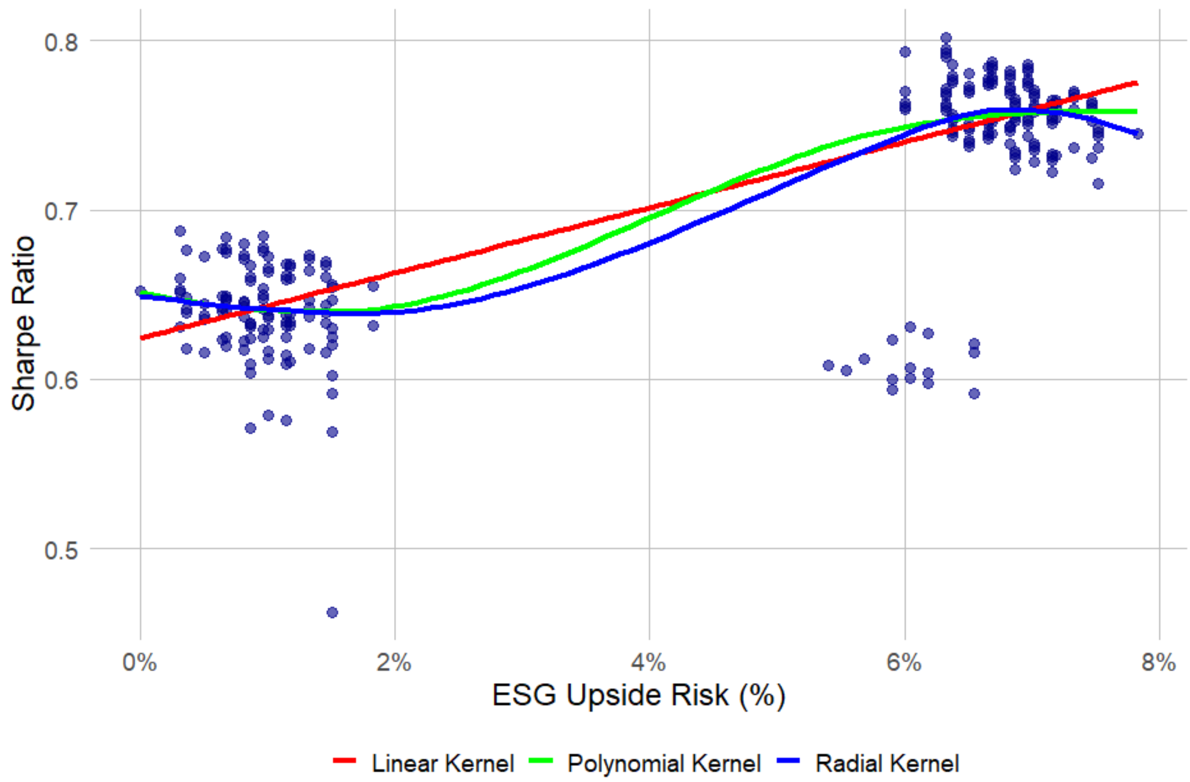

Figure 5. Impact of ESG Upside Risk on Sharpe Ratio Across SVM Kernels
Source: Own editing

These contrasting profiles are summarised in Table 8, which compares the risk metrics of the best- and worst-performing portfolios.

Table 7. Comparative Risk Profiles of the Best and Worst Performing Portfolios.

Scenario	Asset	Weight	Risk (Std. Dev)	Downside Risk	Adjusted Upside Risk
Worst Case (Sharpe ratio of 0.4625)	ICLN	5.00%	32.79%	22.76%	0.50%
	FAN	5.00%	24.57%	17.32%	0.36%
	QCLN	5.00%	41.77%	28.86%	0.65%
	ARKK	5.00%	47.28%	33.32%	0.70%
	FCPGX	80.00%	25.88%	18.80%	5.66%
Best Case (Sharpe ratio of 0.8017)	ESGV	5.00%	21.97%	15.68%	0.31%
	GRID	80.00%	25.63%	18.12%	6.01%
	SPY	5.00%	20.95%	15.01%	0.30%

VTI	5.00%	21.46%	15.41%	0.30%
AGTHX	5.00%	22.68%	16.37%	0.32%

Source: Own editing.

Based on the analysis of the optimised portfolios, both hypotheses were accepted.

1) Diversification Benefit Hypothesis: The data demonstrates that including ESG funds in a traditional portfolio provides diversification benefits by reducing overall portfolio risk without significantly diminishing returns. This supports H1, which posits that ESG funds enhance portfolio stability.

2) Downside Risk Hypothesis: The analysis further indicates that ESG funds exhibit lower downside risk during market downturns compared to traditional funds. This finding aligns with H1, suggesting that ESG factors contribute to resilience during economic or environmental crises.

The exceptional performance of certain assets, such as GRID, introduces an intriguing dynamic in assessing the broader benefits of ESG investments. GRID's substantial contribution to portfolio optimisation underscores how standout ESG assets can disproportionately influence overall portfolio results, creating a perception that ESG assets are more effective than they might be in aggregate.

5. Conclusions

The results of this analysis provide a comprehensive understanding of the performance and risk characteristics of combining ESG and non-ESG assets, highlighting their implications for portfolio optimisation and risk management. The descriptive statistics reveal that while ESG assets generally offer higher average returns, particularly GRID and ESGV, these returns are accompanied by greater volatility. In contrast, non-ESG assets tend to provide steadier performance, making them potentially more appealing to risk-averse investors. However, the higher kurtosis values among both groups underscore a common trait: the potential for significant outlier events, suggesting that extreme downside risks are a concern across the board.

We build a hybrid model that combines combinatorial asset selection with strict minimum and maximum allocation constraints within a mean-variance framework, allowing for the flexible inclusion of both ESG and non-ESG assets while promoting diversification and minimizing risk exposure. The model results demonstrate a significant correlation between ESG asset weight and the Sharpe ratio ($r = 0.7607$), indicating that the inclusion of ESG investments can markedly enhance risk-adjusted returns. Furthermore, SVM kernel analysis reveals that while a linear relationship explains much of the variance, the radial kernel's superior performance ($R^2 = 0.5807$) suggests that non-linear dynamics also play a meaningful role. Additionally, the downside risk analysis indicates that ESG assets contribute to a reduction in downside risk during periods of market decline, thereby reinforcing the resilience of portfolios that incorporate ESG funds.

The analysis also reveals a strong connection between ESG and non-ESG assets, particularly in sectors such as technology and clean energy, indicating that both groups respond to similar market forces. This interconnectedness supports the inclusion of both asset types in a diversified portfolio, allowing them to complement one another despite differing risk-return characteristics. However, the assumption that ESG assets inherently mitigate risk does not always hold true. Our findings show that while ESG funds can deliver improved risk-adjusted returns in certain scenarios, their performance is highly dependent on asset-specific covariances and prevailing market conditions. Furthermore, the outsized contribution of certain ESG assets, such as GRID, highlights how individual assets can disproportionately influence the perceived success of ESG investments.

In summary, the findings indicate that investors and portfolio managers may achieve enhanced portfolio performance by incorporating ESG assets, capitalizing on their potential for superior returns while potentially mitigating downside risk under conditions of market volatility. This effect is particularly evident when ESG and non-ESG assets overlap in the same sectors, offering a balanced buffer against sector-specific market fluctuations. As the financial landscape increasingly prioritizes sustainability, the role of ESG investments in portfolio optimisation is expected to gain significance. This evolution necessitates further empirical investigation into the long-term implications of ESG asset inclusion on overall portfolio performance and the refinement of risk management strategies.

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