Belgrade School of Computing

MASTER IN COMPUTATIONAL FINANCE

Master thesis

ESG investing using expected shortfall as a measure of risk

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Abstract

ESG stands for Environmental, Social, and Governance. ESG investing refers to the practice of incorporating environmental, social, and governance factors into the investment decision process. Amid growing global awareness and demand for sustainable practices, ESG investing has witnessed a significant growth.

This study examines the impact of Environmental, Social, and Governance (ESG) scores on the risk and returns of investment portfolios through empirical analysis, with a particular focus on the Expected Shortfall (ES) as the measure of risk. It compares the performance of portfolios that adhere to ESG criteria with those that do not. The goal is to determine whether incorporating ESG principles into investment strategies can reduce the potential for losses and enhance financial returns. The research seeks to provide concrete evidence on how ESG investing can contribute to risk reduction and possibly increase returns for investors.

1.Introduction

“Of all the varying concerns that make up the social responsibility component of SRI, the environment is the most fundamental. Philosophically speaking, if the Earth’s ability to life is essentially impaired, there seems little point in worrying about the other issues.”(Sparkes, 2010)

The term ESG first appeared in 2004 in a report titled 'Who Cares Wins.' This report, a joint initiative by financial institutions at the invitation of the United Nations, marked the beginning of its growth in popularity and influence.

Over the years, various concepts have been used to measure the effect of sustainability on financial performance, including corporate social responsibility (CSR), socially responsible investing (SRI), and responsible investing (RI). The most recent and relevant measure today is ESG, which assesses a company's performance in terms of environmental, social, and governance conditions.

Today, global ESG assets surpassed $30 trillion in 2022 and are on track to surpass $40 trillion by 2030 — over 25% of projected $140 trillion assets under management (AUM). (“Global ESG Assets Predicted to Hit $40 Trillion by 2030, despite Challenging Environment, Forecasts Bloomberg Intelligence | Press | Bloomberg LP,” n.d.).

The rising interest in sustainable investing and finance, and the related focus on ESG reporting, has begun to reshape not just equity markets but the world of fixed income investments as well. So-called green bonds, for example, grew from $2.6 billion in 2012 to $257.7 billion in 2019.(*2019 Green Bond Market Summary*, 2020)

As noted by (Giese et al., 2019) we can break down ESG investing into three main areas that each have their own investment objective: First, ESG integration, in which the key objective is to improve the risk–return characteristics of a portfolio. Second, values-based investing, in which the investor seeks to align his portfolio with his norms and beliefs. Third, impact investing, in which investors want to use their capital to trigger change for social or environmental purposes, for example, to accelerate the decarbonization of the economy.

The term ESG investing started becoming very polarized, but no single term could ever accurately capture the range of issues that can have a significant impact on a given business's efforts to maximize long-term value.

Previous studies on ESG mostly focus on the overall ESG score and lack an in-depth examination of ESG components: environmental (E), social (S), and governance (G). In this thesis, we not only examine the influence of the ESG score on portfolio performance but also consider the individual scores of each ESG component on the portfolio.

Milton Friedman argued that a corporation's primary objective should be to maximize profits (Friedman, 2007) and that “the social responsibility of business is to increase its profits” . While the majority of corporate executives, boards, and investment managers still agree with Friedman's view, many others, after 50 years, believe this is not the whole answer. (Hill, 2020)

The popular wisdom has been that ESG investors would have to accept a lower return from their “virtuous” portfolios. This assumption is no longer universally accepted and empirical evidence, although mixed, seems in most cases to support the contention that ESG investing does not have to underperform traditional portfolios. (Hill, 2020)

We will try to answer the question of whether it is possible “to do well while doing good” as suggested by Hamilton, so that investors can enjoy a moral as well as monetary payoff. (Hamilton et al., 1993)

Over the years, many researchers from both academia and the asset management industry have examined the relationship between the ESG profiles of companies and their financial risk and performance characteristics. (Giese et al., 2019)

This study examines the impact of Environmental, Social, and Governance (ESG) scores on the risk and returns of investment portfolios through empirical analysis, with a particular focus on the Expected Shortfall (ES) as the measure of risk. It compares the performance of portfolios that adhere to ESG criteria with those that do not. The goal is to determine whether incorporating ESG principles into investment strategies can reduce the potential for losses and enhance financial returns.

Value at risk (VaR) and expected shortfall (ES) are attempts to provide a single number that summarizes the total risk in a portfolio, but regulators are increasingly recognizing the advantages of ES and are are switching to ES for market risk (Hull, 2015)

VaR is a popular risk measure that asks the question “How bad can things get?” However, it is more useful to know “If things do get bad, how much can the company expect to lose?”

Expected Shortfall (ES) answers that question and we will use Expected Shortfall as a measure of risk in our analysis. Unlike VaR, which disregards losses beyond a selected confidence level, ES incorporates information from the entire loss distribution, especially the "fat tails" where catastrophic events reside. (McNeil et al., 2015)

Unlike traditional risk metrics such as volatility or Value at Risk (VaR), Expected Shortfall provides a more comprehensive view of potential losses by focusing on the tail end of the distribution of returns. This makes ES particularly suited for evaluating the risk-reduction capabilities of ESG investing, as it captures the magnitude of potential extreme losses.

Central to this analysis is the application of Expected Shortfall as the primary risk measure, employing a 97.5% confidence level as proposed by Basel IV regulations.

The goal of this thesis is two-fold. First, we want to assess how implementing ESG scores affects portfolio performance and the risk profile of portfolios we analyze, specifically focusing on the expected shortfall measure of risk. Second, we explore what happens to portfolio performance when we implement multi-objective evolutionary algorithm.

The rest of this paper is structured as follows: in Section 1.1 we do literature overview where we review papers that investigate impacts of ESG scores on (CFP) corporate financial performance, then in section 1.2 we go through ESG evolution from it’s origins to ESG becoming mainstream, in section 1.3 we talk about Risk measures in finance and Expected shortfall, in section 1.4 we go into Multi-Objective Evolutionary Algorithms (MOEAs) and their application in portfolio optimization. In Section 2, we describe the data sources and methods used to construct the portfolios for this thesis. Section 3 presents the empirical results of our analysis, comparing the performance and risk metrics of different portfolios. Section 4 concludes with a discussion on the implications of ESG integration in portfolio management and suggestions for future research.

1.1 Literature Overview

There is still no agreement whether sustainability leads to higher returns. Research shows evidence of positive, negative, and neutral impacts on returns from sustainability. To provide our thesis with an empirical context, we will present some of the existing literature on ESG investing.

(Endrikat et al., 2014) conducted a meta-analytic review covering 149 studies and found that the relationship between environmental performance and financial performance is positive and partially bidirectional and also stronger in case of a proactive strategic approach, furthermore having a good sustainability record shows a positive effect on the financial performance; therefore, the corporations should adopt sustainability practices and integrate them into their business processes, and this will benefit shareholders as well as other stakeholders. The finding that total ESG score has significant positive effect on financial performance implies that the corporations should be conscious of environmental issues, be more responsive to the society in which they operate, and also have good corporate governance practices.

Through analyzing what is by far the most comprehensive dataset on existing ESG–CFP research to date, we find that the business case for ESG investing is empirically well founded. Investing in ESG pays financially. Furthermore, we highlight that the positive ESG impact on CFP is stable over time. Based on the data, we are able to derive conclusions for portfolio and nonportfolio studies, 3 different asset classes, regions, and categories of E, S, and G. Particularly promising results are obtained when we differentiate between regions, nonportfolio studies, and asset classes other than equities. About 90% of the studies find a non-negative relation between ESG and Corporate Financial Performance (CFP) and majority of the 90% are in fact positive. (Friede et al., 2015)

Other academics argue that sustainable and responsible business practices impact financial performance negatively.

(Zahid et al., 2022) argue that ESG score and its components have a statistically significantly negative effect on ROA. The social and governance scores have a significantly positive impact on revenue, whereas the overall ESG and environmental components are not significantly related to revenue. ESG and its components have a negative effect on ROA, showing that the expense of

ESG practices becomes a cost to shareholders, limiting investment opportunities and overall performance.

Long et al. noted that ESG investing fails to generate abnormal returns unconditionally in large international market sample. They observed no evidence of systematic and reliable alphas on long-short ESG portfolios in global markets. If abnormal returns exist—scattered across a handful of markets—they are more likely to be negative than positive. In short, investors should not expect superior returns from investing in ESG stocks (Long et al., 2024)

Also, (Hartzmark & Sussman, 2019) analyzed the Morningstar sustainability ratings of more than 20,000 mutual funds representing over $8 trillion of investor savings. Although the highest rated funds in terms of sustainability certainly attracted more capital than the lowest rated funds, none of the high sustainability funds outperformed any of the lowest rated funds.

Interestingly, out of 253 funds that switched to an ESG focus in 2020 in the US, 87 per cent of them rebranded by adding words such as “sustainable” or “ESG” or “green” or “climate” to their names. None changed their stock or bond holdings at that point. (Eco-Business, 2021)

As noted in a meta-analysis by (Atz et al., 2020), returns from ESG investing documented in the literature are not different on average from returns from conventional investments.

As stated by (Waddock & Graves, 1997), there are so many intervening variables between social and financial performance, that there is no reason to expect a relationship to exist, except by chance.

And further, (Halbritter & Dorfleitner, 2015) conclude that ESG portfolios do not show significant return differences between companies featuring high and low ESG rating levels. This applies both to the overall scores and to the particular pillars.

In conclusion, the existing body of research on the financial impacts of ESG investing presents a varied landscape of outcomes, with studies revealing positive, negative, and neutral effects on returns.

In conclusion, the studies that have been conducted on the financial impacts of ESG investing identify different outcomes, with research revealing positive, negative, and neutral effects on returns.

1.2 Environmental, Social, and Governance (ESG)

Sustainable finance has its roots in the broader movement of socially responsible investing (SRI), which emerged in the 1960s and 1970s. It was driven by the desire to avoid investments in industries such as tobacco, weapons, and those involved in the South African apartheid regime. Investors began to exclude stocks or entire industries from their portfolios based on moral values.

The main focus was on negative screening, that is, excluding certain sectors or companies from investment portfolios based on ethical considerations.

As an investment strategy, SRI removes “sin” stocks such as tobacco, alcohol, and weapons from portfolios with negative screens. Values aside, this is potentially risky due to a lack of portfolio diversification. SRI therefore got somewhat of a bad rep for being “values-based investing” in mainstream finance circles. (*Sustainability in South Africa*, n.d.) But contrary to what mainstream investors might think, environmental, social, and governance (ESG) investing, on the other hand, is not some virtuous strategy relegated to those investors who are willing to put their beliefs before their returns. ESG can simply be a prudent approach to encompassing a broader information set that focuses on material issues with the potential to affect the long-term viability of company business models.

In the 1980s and 1990s, the scope of SRI expanded. Investors began to incorporate environmental, social, and governance (ESG) criteria into their investment decisions and to actively seek out companies to invest in that met certain environmental, social, or governance standards. The launch of the Domini 400 Social Index in 1990, which later became the MSCI KLD 400 Social Index, was a significant milestone.

This shift marked the beginning of investors not only avoiding harm but also seeking to do good by supporting companies with positive social and environmental impacts, “to do well while doing good”.

By the 2000s, ESG criteria started to be recognized by mainstream investors. Large asset owners began to acknowledge the importance of ESG data in assessing long-term risks and opportunities. This recognition was driven by the growing awareness of global challenges such as climate change, resource scarcity, and social inequality. In 2006 The Principles for Responsible Investment (PRI) were developed in response to the increasing relevance of environmental, social, and corporate governance (ESG) issues to investment practices.

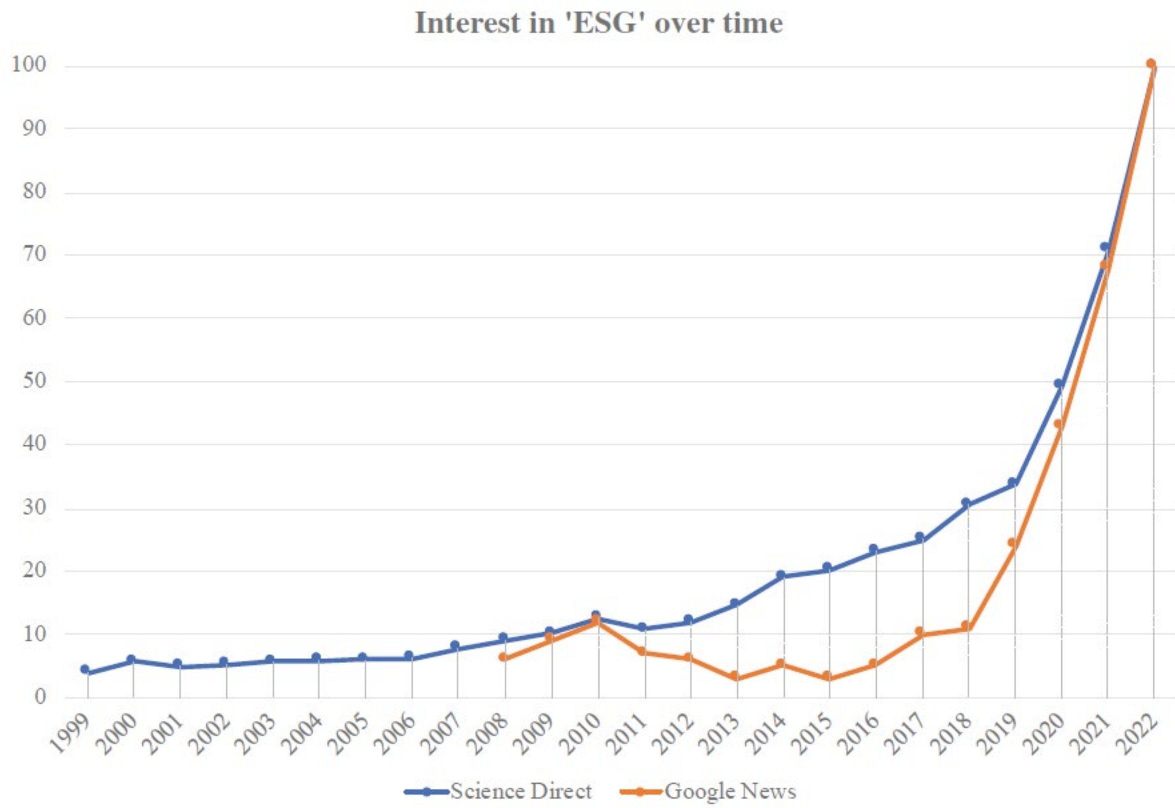

Figure 1 Interest evolution in the term 'ESG' in academic studies and press. Source Authors' elaboration on data from SciencedDirect.com (published articles) and Google Trends (News searches). (Gaganis et al., 2023)

There are six Principles for Responsible Investment, outlined as follows: (*What Are the Principles for Responsible Investment?*, n.d.)

Principle 1: We will incorporate ESG issues into investment analysis and decision-making processes.

Principle 2: We will be active owners and incorporate ESG issues into our ownership policies and practices.

Principle 3: We will seek appropriate disclosure on ESG issues by the entities in which we invest.

Principle 4: We will promote acceptance and implementation of the Principles within the investment industry.

Principle 5: We will work together to enhance our effectiveness in implementing the Principles.

Principle 6: We will each report on our activities and progress towards implementing the Principles.

By the late 2010s, ESG investing had seen substantial growth and began to accelerate appreciably, with significant increases in assets under management considering ESG factors.

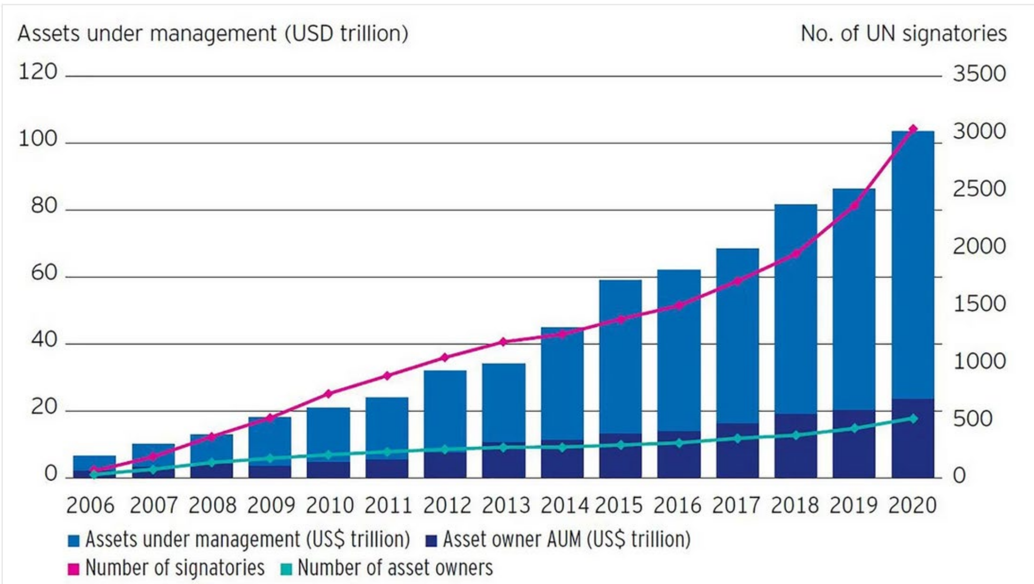

Figure 2 Growth of Assets Under Management (AUM) and PRI signatories Source: UN PRI Association.

ESG investing aims to correctly identify, evaluate, and price social, environmental, and economic risks and opportunities.

Environmental Factors are factors pertaining to the natural world. These include the use of and interaction with renewable and non-renewable resources (e.g., water, minerals, ecosystems, and biodiversity).

Social Factors affect the lives of humans. The category includes the management of human capital, non-human animals, local communities, and clients.

Governance Factors involve issues tied to countries and/or jurisdictions or are common practice in an industry, as well as the interests of broader stakeholder groups. (Simonek & Verhagen, 2022)

Overview of different ESG factors according to (Clark et al., 2014):

Environmental (“E”)	**Social (“S”)**	**Governance (“G”)**
Biodiversity/land use	Controversial business	Accountability
Carbon emissions	Customer relations/product	Anti-takeover measures
Climate change risks	Diversity issues	Board structure/size
Energy usage	Employee relations	Bribery and corruption
Raw material sourcing	Health and safety	CEO duality
Regulatory/legal risks	Human capital management	Executive compensation schemes
Supply chain management	Human rights	Ownership structure
Waste and recycling	Responsible marketing and R&D	Shareholder rights
Water management	Union relationships	Transparency

Modern Portfolio Theory has given us the twin concepts of risk and return in evaluating investment portfolios. The advent of ESG investing adds a third leg. An efficient portfolio frontier can now be conceptualized as a three-dimensional surface, optimizing risk, return, and social impact. (Hill, 2020)

1.3 Risk Measures in Finance

One of the central challenges in modern risk management is assessing risk. (Doherty, 1985) defined risk as the "lack of predictability of outcomes".

(McNeil et al., 2015) defines risk as "Any event or action that may adversely affect an organization's ability to achieve its objectives and execute its strategies or, alternatively, the quantifiable likelihood of loss or less-than-expected returns".

Risk, in a financial context, refers to the potential for losing financial investment or facing financial instability. Managing financial risk, therefore, is primary concern for investors and financial managers.

Most financial professionals seek to manage capital to achieve selected outcomes on a scale of risk and return. Some examples of investment products along this spectrum are:

- Low risk/low returns: U.S. Treasury Bonds (currently yields 0.5–2.5% in the United States and negative yields in Europe).
- Modest risks/modest returns: Investment-grade corporate bonds (currently 2.5–5%).
- Medium risk/medium returns: Publicly traded equities (a.k.a. the "stock market") where the average return over many decades has been about 7%.
- High risk/high returns: Private equity investments seeking returns greater than 15%, and venture capital seeking rates of return of 40% and more. (Eckhart, 2020)

Modern Portfolio Theory (Fabozzi et al., 2002), introduced by Harry Markowitz in 1952, is concept in finance that focuses on how investors can construct portfolios to maximize expected return relative to market risk. Modern portfolio theory tells that the risk and return of portfolio are not based solely on the performance of individual components but also on how each other components interacts with each other through diversification. This interaction if quantified using covariance – a measure of how tow assets move in relation to each other. Markowitz suggests minimizing variance and maximizing mean of the portfolio, simultaneously, to get the best portfolio. (Kandasamy, 2008)

In the field of finance, two widely employed risk measures are Value at Risk (VaR) and Conditional Value at Risk (CVaR), also known as Expected Shortfall. CVaR is generally regarded as a superior approximation of potential losses compared to VaR. These risk measures are typically calculated (or, more precisely: “estimated”) at three different confidence intervals: 95%, 99%, and 99.99%. For the purpose of this thesis, we will adhere to the 97.5% level as specified by the Basel Committee.

Value-at-risk (VaR) has become a standard measure used in financial risk management due to its conceptual simplicity, computational facility, and ready applicability (Yamai & Yoshiba, 2002), but as (Artzner et al., 1999) noted, VaR has shortcomings (1) VaR measures only percentiles of profit-loss distributions, and thus disregards any loss beyond the VaR level (we call this problem “tail risk”), and (2) VaR is not coherent since it is not sub-additive.

The main disadvantage of VaR method is the fact that it cannot estimate the important loses, because many times, the distributions have fat tails, characterized by a large number of unexpected events that do not follow a normal distribution. (Trenca et al., 2015)

To address the shortcomings and limitations associated with Value at Risk (VaR) (Artzner et al., 1999) have proposed the use of expected shortfall.

Expected shortfall is defined as the conditional expectation of loss given that the loss is beyond the VaR level. By its definition, expected shortfall considers the loss beyond the VaR level. Also, expected shortfall is proved to be sub-additive, which assures its coherence as a risk measure. On these grounds, some practitioners have been turning their attention toward expected shortfall and away from VaR. (Yamai & Yoshiba, 2002)

VaR is generally defined as "possible maximum loss over a given holding period within a fixed confidence level." Mathematically, the VaR at the $100(1 - \alpha)$ percent confidence level is defined as the lower 100α percentile of the profit-loss distribution. This means it is the value at which you expect the loss to be exceeded with only a α percentage probability. In other words, there is a $(1-\alpha)$ probability that the loss will not exceed this VaR value. For example, if $\alpha = 0.05$ (5%), the 95th percentile (100(1-0.05) percent) of the loss distribution will be your VaR. This states that there is a 95% confidence that your losses will not exceed this VaR level within the specified period, while there's a 5% chance that the losses could be worse than the VaR estimate.

Expected Shortfall (ES) at the same $100(1 - \alpha)$ percent confidence level is the average of all losses that exceed the VaR in the worst 100α percent of cases. It captures not just the threshold of worst-case losses (like VaR), but also the average outcome of these losses, providing a more conservative view of potential risk. For instance, using the same $\alpha = 0.05$, ES would consider the mean loss in the worst 5% of outcomes. This offers a clearer insight into the severity of losses that could occur beyond the VaR, highlighting both the frequency and intensity of extreme losses.

In simple terms, for illustration, if VaR(95) is equal to 3%, it indicates that there is a 5% probability that the portfolio will experience a loss of 3% or greater. Conversely, if CVaR(95) is equal to 4.5%, it signifies that within the worst 5% of portfolio returns, the average loss will be 4.5%. Thus, CVaR provides an estimate of the average expected loss. It is important to note that VaR may lead to an underestimation of potential losses due to its disregard for returns that are more severe than the specified VaR level.

Figure 3 illustrates the concepts of VaR and CVaR

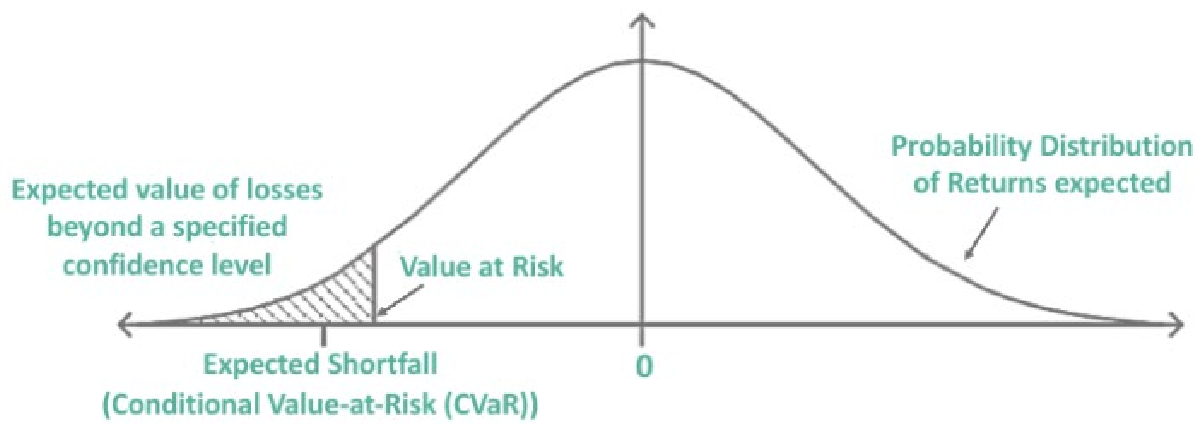

Figure 3 concepts of Value at Risk (VaR) and Expected Shortfall (CVaR) within a probability distribution of expected returns (Choubey, 2023)

We will also present VaR and CVaR mathematical formulations:("Understanding the Paper "Expected Shortfall," 2023)

$$x^{\alpha} = \sup\{x \mid P[X \leq x] \leq \alpha\}$$

where:

- x^{α} represents a value of x raised to the power of α
- sup stands for supremum, which is the least upper bound of set
- $P[X \leq x]$ $represents\ the\ probability$ $that\ the\ random\ variable\ X\ is\ less\ than\ or\ equal$ to x
- $the\ condition\ P[X \leq x] \leq \alpha\ means\ we\ are\ considering\ all$ $x\ such\ that\ the\ probability\ of\ X\ being\ less\ than\ or\ equal\ to\ x\ is\ less\ than\ or\ equal\ to\ \alpha$

$$ES_{\mathrm{\alpha}} = -\frac{1}{1-\mathrm{\alpha}}\int_{-\infty}^{-VAR_{\mathrm{\alpha}}} x\, f(x)\, dx$$

where:

- $f(x)\ is\ the\ probability\ density\ function\ of\ the\ loss\ distribution$
- $VAR_{\mathrm{\alpha}}\ is\ the\ Value\ at\ Risk\ at\ the\ \alpha\ confidence\ level$
- $x\ represents\ the\ losses$

1.4 Multi-Objective Evolutionary Algorithms (MOEAs)

Genetic algorithm is a stochastic optimization technique invented by Holland (1975) based on the Darwin principle that in the nature only “the fittest survive”. The main idea of Holland’s theory is the application of the basic phenomena of the biological evolution such are inheritance, crossover and mutation, in order to find (generate) solution that best fits. In the case of portfolio optimization problems, term “the fittest” corresponds to optimal portfolio. (Ranković et al., n.d.)

Studies have increasingly employed genetic algorithms (GAs) for addressing various constraints and risk measures in portfolio optimization.) (Arnone et al., 1993) utilized GAs for optimizing portfolios with a focus on downside risk measures, also (Oh et al., 2005) explored GAs for index fund management portfolio optimization, and recently (Anagnostopoulos & Mamanis, 2011) presented an analysis of the applicability of advanced multiobjective evolutionary algorithms for tackling the bi-objective portfolio optimization problem, focusing on maximizing expected returns while minimizing risk.

Genetic algorithms are heuristic search methods inspired by nature. They can be used to find solutions to optimization problems where there are no “good” deterministic search methods. Principles of evolutionary biology, such as natural selection and reproduction serve as guidelines to evolve a population of solutions to a given problem. (Roudier, 2007)

Portfolio optimization is very complicated as it depends on many factors such as assets interrelationships, preferences of the decision makers, resource allocation and several other factors. As a result, the decision maker has to take several issues into consideration. These issues are conflicting which makes the problem as a multi-objective one. In fact all practical optimization problems, especially economical design optimization problems have a multi-objective nature much more frequently than a single objective one. (Mishra et al., 2009)

The presence of multiple objectives in a problem, in principle, gives rise to a set of optimal solutions (largely known as Pareto-optimal solutions), instead of a single optimal solution. In the absence of any further information, one of these Pareto-optimal solutions cannot be said to be better than the other. This demands a user to find as many Pareto-optimal solutions as possible.

Multiobjective evolutionary algorithms (EAs) that use nondominated sorting and sharing have been criticized mainly for:

1. $O(MN^3)$ computational complexity (where M is the number of objectives and N is the population size);
2. nonelitism approach;
3. the need for specifying a sharing parameter;

In this thesis we use nondominating sorting genetic algorithm II (NSGA-II), which alleviates all the above three difficulties.

NSGA-II is an evolutionary algorithm created to address the limitations of earlier versions of evolutionary algorithms. (Deb et al., 2002)

Like all other evolutionary algorithms, NSGA-II starts with a set of randomly generated candidate solutions, referred to as a population. In each of the iterations (generations), a set of new candidate solutions (offspring solutions) is generated by applying the evolutionary processes consisting of selection, crossover and mutation. By performing these processes over a number of generations, the solutions evolve and improve in terms of the chosen objectives (in our case, minimizing risk and maximizing return). (Drenovak et al., 2022)

It is stimulated by natural selection that is inspired from the theory of Darwin. Hence, the basic idea is to make a population of candidate solutions evolving toward the best solution in order to solve a multiobjective optimization problem. NSGA-II was designed to be applied to an exhaustive list of candidate solutions, which creates a large search space. (Mkaouer & Kessentini, 2014)

The algorithm we use in this thesis addresses a multi-objective problem where the percentage of each available asset is selected to simultaneously maximize return and minimize risk, simultaneously, and that portfolio optimization problem can be defined as follows:

$$\min Sharpe(x) = -\left(\frac{r_p - r_f}{\sigma_p}\right) \tag{1}$$

$$\text{subject to} \sum_{i=1}^{N} x_i = 1 \tag{2}$$

$$0 \leq x_i \leq 1, \quad i = 1, \ldots, N \tag{3}$$

In these expressions, x denotes the vector of portfolio weights x_i and $Sharpe(x)$ represents the Sharpe ratio of the portfolio, where r_p is the expected portfolio return, r_f is the risk-free rate, and σ_p is the portfolio standard deviation. The Sharpe ratio is maximized, which effectively involves minimizing its negative as shown in the objective function.

Equation (2) enforces the budget constraint, ensuring the sum of portfolio weights equals 1. Equation (3) stipulates that no short sales are permitted, bounding the weights to be non-negative and no greater than 1.

This model is a bi-objective optimization problem, focusing on minimizing risk and maximizing return, adjusted for the risk-free rate, using the Sharpe ratio as the performance metric. The model aims to find the optimal set of weights x_i that maximize the Sharpe ratio, indicating efficient risk-adjusted returns.

Flowchart of NSGA-II algorithm used in this thesis is shown in Figure 2.

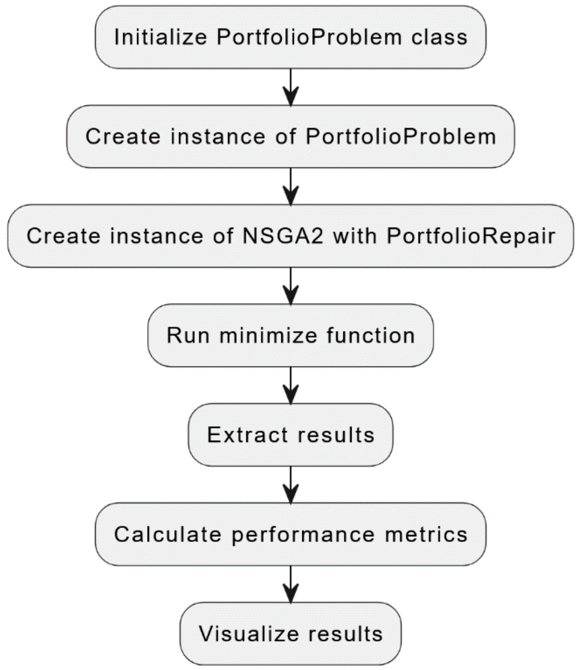

Figure 4 Algorithm flowchart

2. Data

The primary objective of this thesis was to understand how portfolios with varying degrees of ESG constraints performed compared to those without such constraints.

We retrieved monthly ESG scores from YahooFinance. ESG data is provided by Sustainalytics, Inc.

Sustainalytics provides data on over 70 indicators. Each indicator is weighted by an assessment of its relative importance in each of 42 industry groups. The indicators are organized in three "pillars" of E, S, and G issues. Each company rated is scored on each factor according to its preparedness, disclosure, and performance relevant to that factor. The resulting scores are scaled between 1 and 100 and each company is then assigned a percentile ranking within its industry group. This process is updated annually. While there is a huge amount of detail and effort in these rankings, there is obviously a substantial amount of judgement required for the underlying qualitative assessments. Yet, one would expect that these judgements would be more objective than those coming from self-reporting by organizations. In additionto these ESG ratings, Sustainalytics also monitors daily news feeds for any events that may have negative impacts. This service allowed Sustainalytics to provide early warning of Volkswagen's scandal relating to falsified diesel emissions testing. (Hill, 2020).

We retrieved historical stock price data for a sample of 50 companies from the S&P 500 index using the Yahoo Finance API through the yfinance library.The retrieved stock price data was processed to handle missing values and ensure consistency. The ESG scores were stored in separate DataFrames for each pillar (E, S, G), combined ESG score and no ESG constrained portfolio.

These subsets allow for the analysis of the individual impact of each ESG pillar on portfolio performance.

For portfolio optimization, the expected returns were calculated using an exponentially weighted historical return model, and the covariance matrix was derived using the Ledoit-Wolf shrinkage estimator(Ledoit & Wolf, 2004) implemented in the PyPortfolioOpt library. The efficient frontier was then constructed using CVXPY, a Python library for convex optimization, to maximize the return risk ratio according to the predefined constraints on the portfolio weights.

Further, we applied an ESG screening process. This screening involved setting a threshold at the 30th percentile of the mean ESG scores, and only stocks above this threshold were considered for the creation of ESG-constrained portfolios. This process was repeated separately for environmental, social, and governance scores to analyze the impact of each ESG aspect independently.

We calculated the Value at Risk (VaR) and Expected Shortfall (ES) for each individual portfolio strategy using historical return data.These risk metrics were estimated to measure the tail risk and the potential for extreme losses, providing risk assessment of each portfolio. The results are visualized for comparison of risk profiles.

And in the second part of our analysis we employ NSGA2 algorithm from pymoo library on our ESG subset with objective to minimize the expected risk and maximize the expected return of the portfolio to see how it performs compared to all other portfolios.

3. Analysis and results

Now, we will present and discuss the empirical results of this thesis.

Table 1 presents the performance of all the portfolios we analyzed. The results show that the NSGA-II Optimized ESG Portfolio had the highest performance at 102.38%. The portfolio without ESG constraints followed with a performance of 78.34%. Portfolios with individual ESG constraints showed varied performance: Environmental (E) constrained portfolio resulted in 72.00%, Social (S) constrained portfolio resulted in 68.69%, and Governance (G) constrained portfolio had the lowest performance at 58.64% when looking at ESG constrained portfolios. The ESG combined portfolio performed at 67.38%. The SPY Benchmark had a performance of 50.89%.

Table 1 Performance comparison of portfolios we analyzed in this thesis

No ESG Constraints	78.34%
E	72.00%
S	68.69%
G	58.64%
ESG	67.38%
NSGA-II Optimized ESG Portfolio	102.38%
SPY Benchmark	50.89%

Table 2 Volatility, measured as the sample standard deviation of returns, for the portfolios we analyze

No ESG Constraints	0.69%
E	0.69%
S	0.68%
G	0.68%
ESG	0.67%
NSGA-II Optimized ESG Portfolio	0.75%
SPY Benchmark	0.80%

Table 2

All portfolios exhibit very similar volatility levels, except SPY benchmark portfolio and NSGA-II Optimized ESG Portfolio that showed higher volatility.

Table 3 Summary statistics for the portfolios we analyzed in this thesis

Portfolios	Cumulative Return	Annual Return	Standard Deviation	Beta	Sharpe Ratio	Skewness	Kurtosis	Maximum Drawdown
No ESG Constraints	78.35%	21.40%	11.06%	0.77	1.63	-0.41	3.76	**-16.01%**
E	72.00%	19.93%	11.08%	0.77	1.52	-0.53	4.2	-14.75%
S	68.69%	19.15%	10.91%	0.75	1.48	-0.57	4.39	-13.93%
G	58.64%	16.72%	10.87%	0.74	1.29	-0.55	3.95	-14.74%
ESG	67.38%	18.84%	10.78%	0.74	1.47	**-0.60**	4.06	-13.68%
NSGA-II Optimized ESG Portfolio	**102.38%**	**26.65%**	11.98%	0.74	**1.87**	-0.36	2.5	-13.68%
SPY Benchmark	50.89%	14.78%	**12.83%**	**1.00**	0.98	**-0.60**	**5.52**	-13.68%

We will now present histograms of portfolio returns with Expected Shortfal and Value at Risk represented as colored vertical lines.

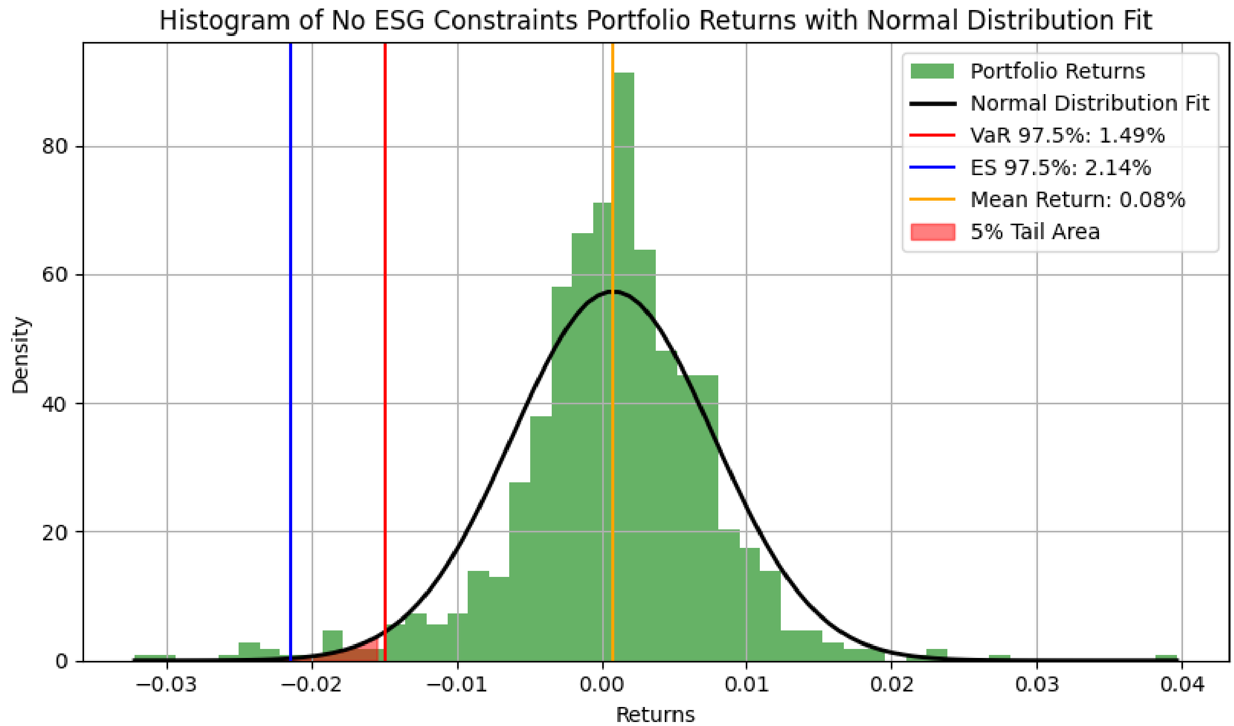

Figure 5 Histogram of No ESG Constraints Portfolio Returns with Normal Distribution Fit

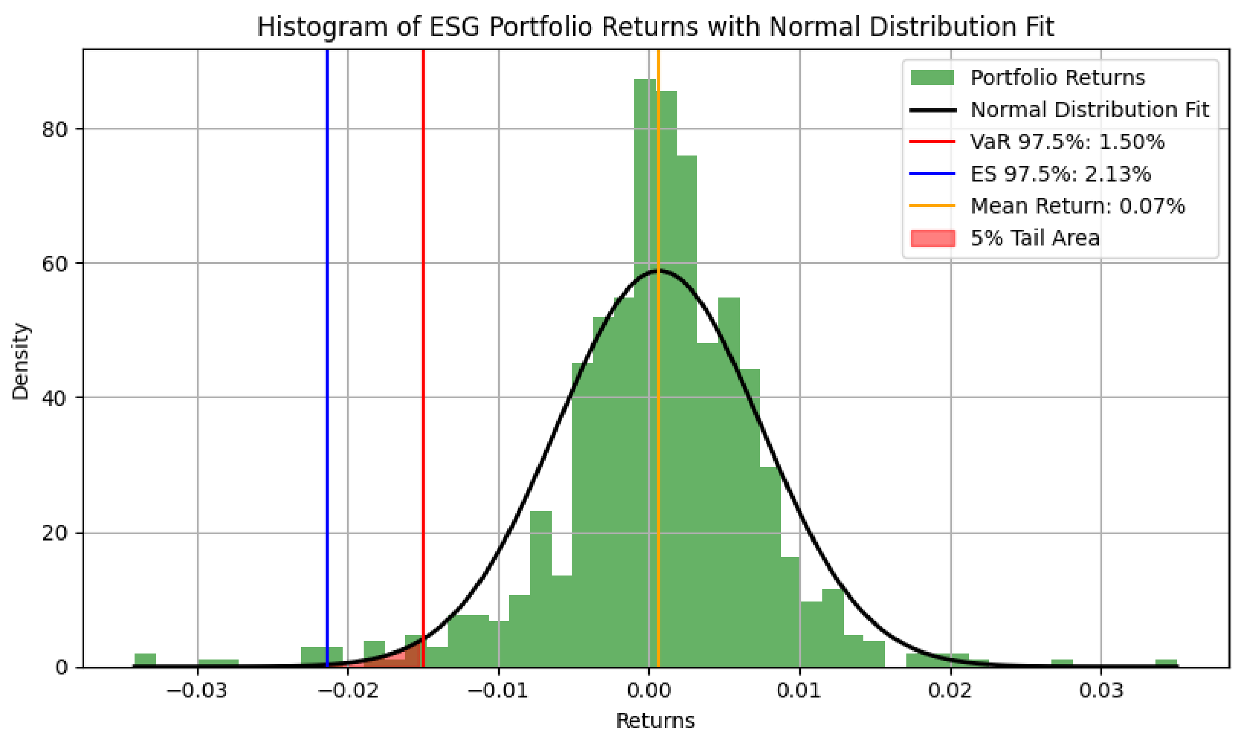

Figure 6 Histogram of ESG Constraints Portfolio Returns with Normal Distribution Fit

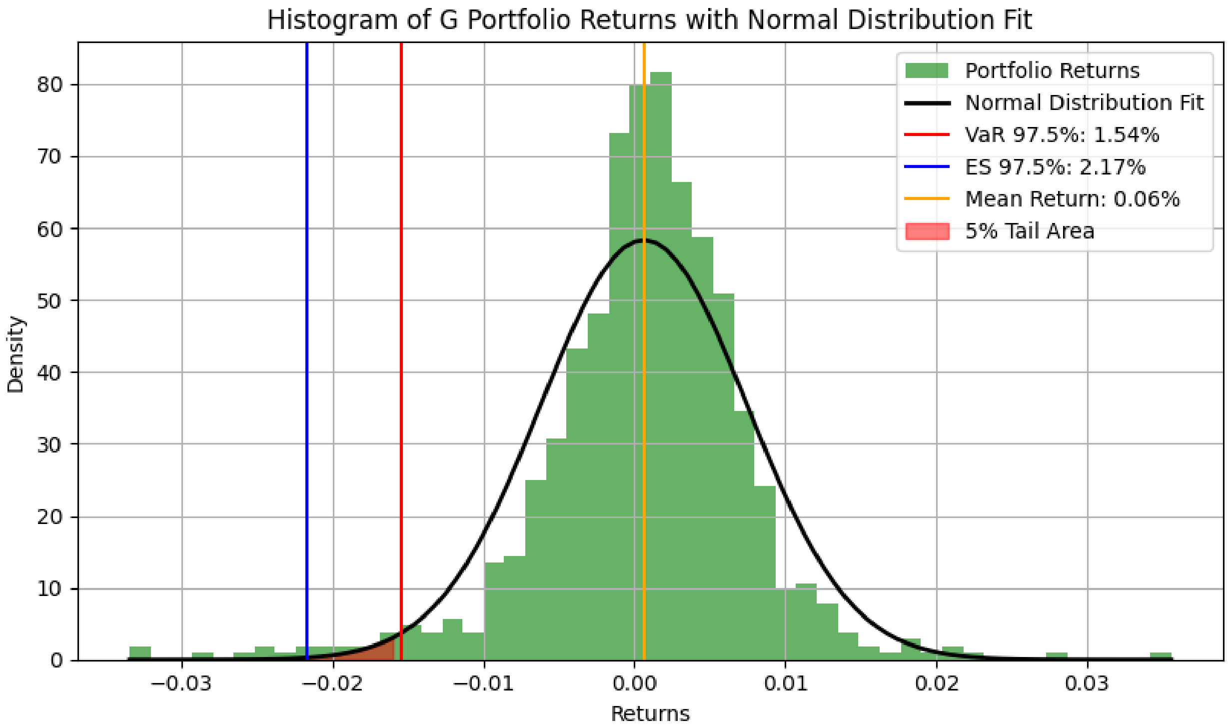

Figure 7 Histogram of G Portfolio Returns with Normal Distribution Fit

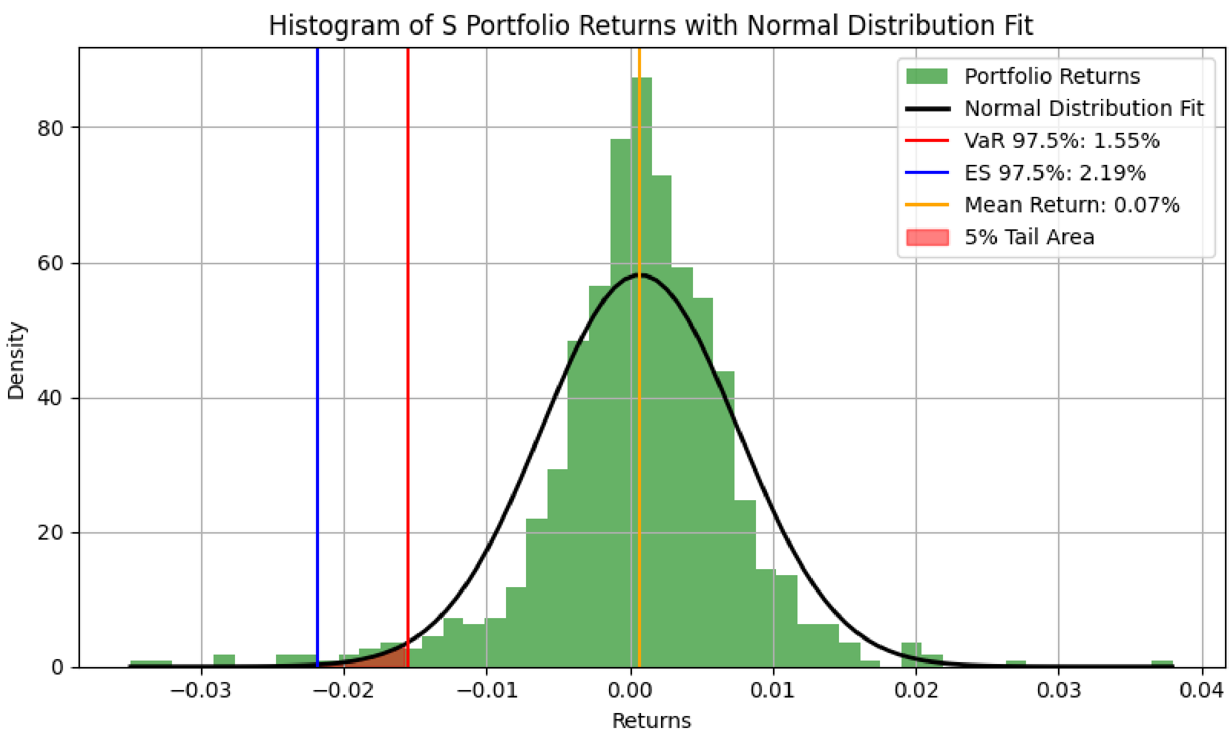

Figure 8 Histogram of S Portfolio Returns with Normal Distribution Fit

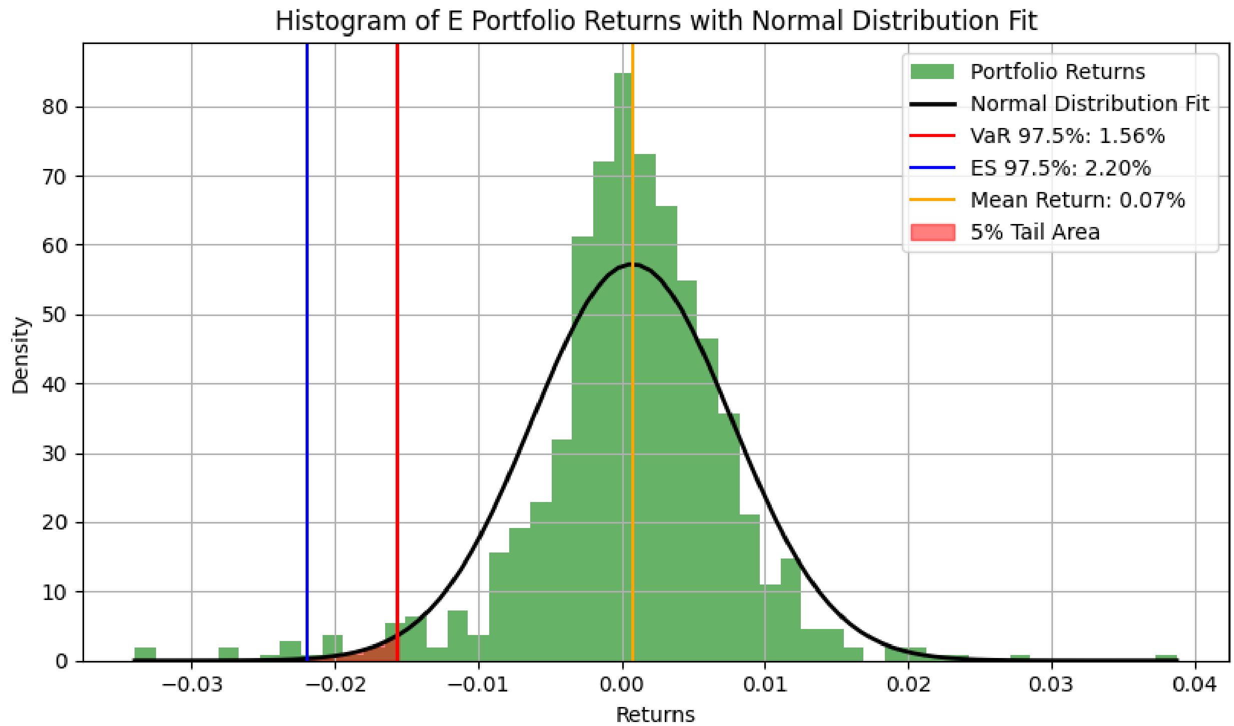

Figure 9 Histogram of E Portfolio Returns with Normal Distribution Fit

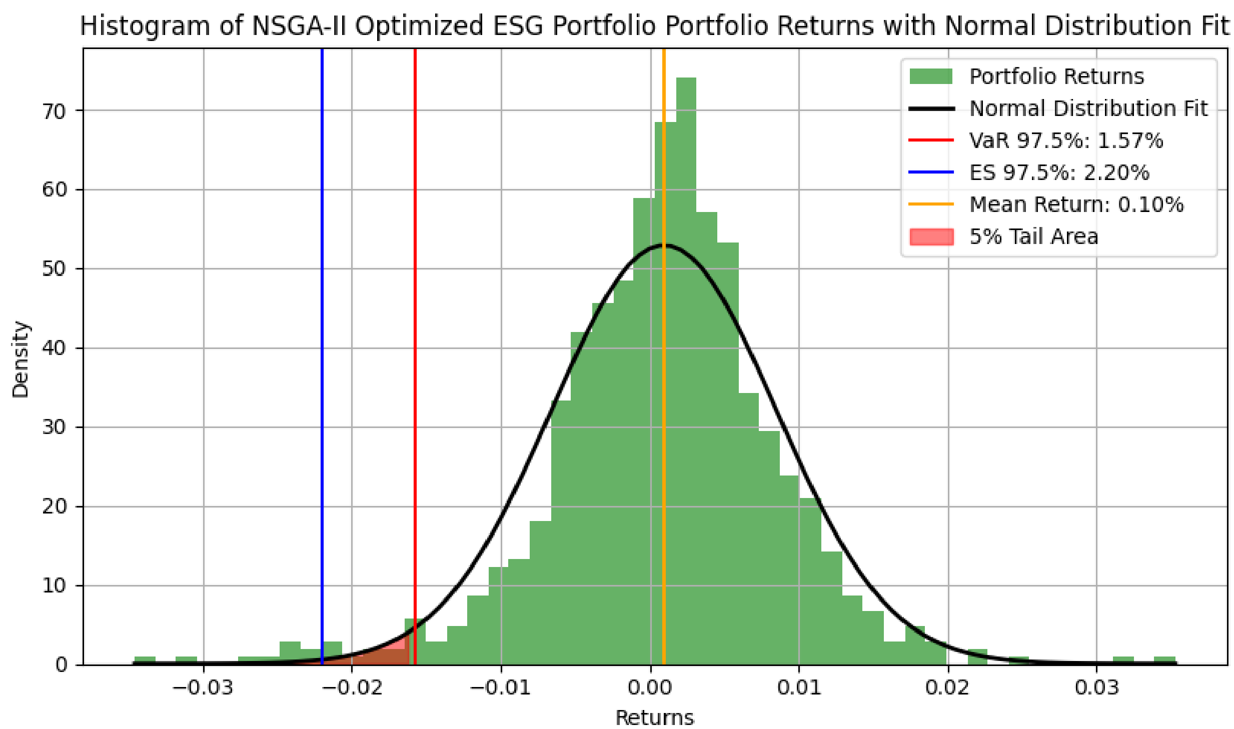

Figure 10 Histogram of NSGA-II Optimized ESG Portfolio Returns with Normal Distribution Fit

Here we present summarized Value at Risk (VaR) and Expected Shortfall (ES) values by portfolios

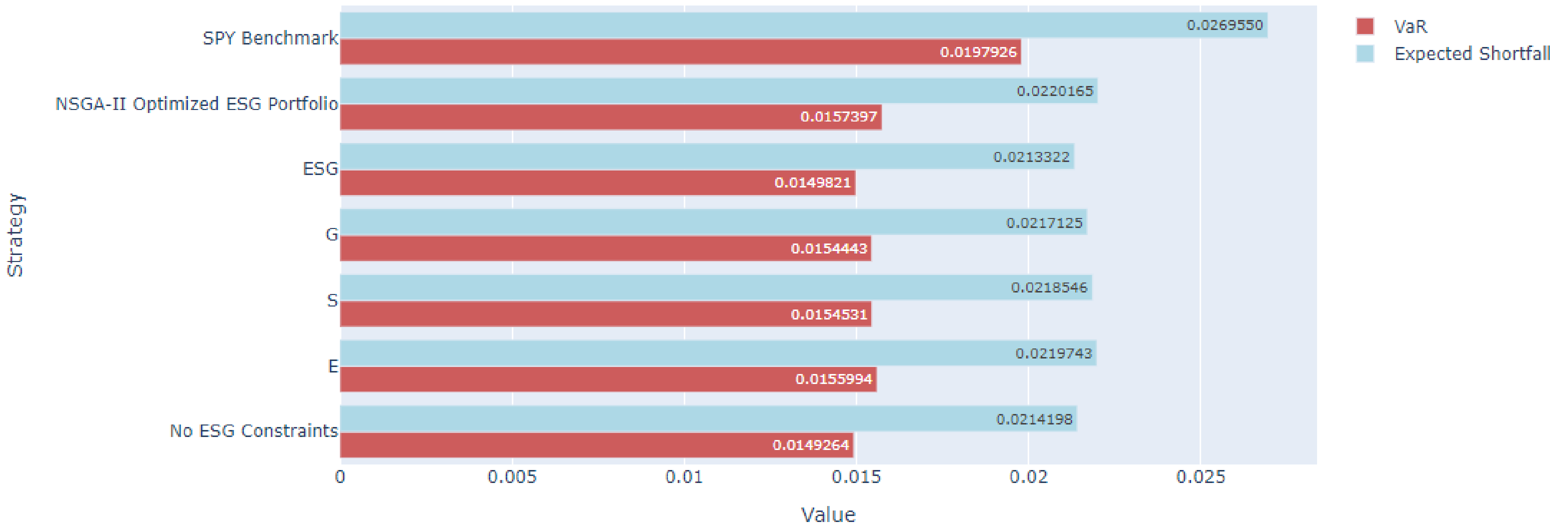

Figure 11 Summary of Value at Risk (VaR) and Expected Shortfall (ES) values

Table 4 Value at Risk (VaR) and Expected Shortfall (ES) measures of portfolios we analyzed in this thesis

Strategy	VaR	ES
No ESG Constraints	**1.49%**	2.14%
E	1.55%	2.19%
S	1.54%	2.18%
G	1.54%	2.17%
ESG	1.49%	**2.13%**
NSGA-II Optimized ESG Portfolio	1.57%	2.20%
SPY Benchmark	1.97%	2.69%

Our findings suggest that the "No ESG Constraints" and "ESG" portfolios exhibit the lowest risk metrics (VaR and ES), indicating they are less likely to experience significant losses, However, their performance is moderate compared to the NSGA-II Optimized ESG Portfolio, which, despite its slightly higher risk metrics, delivers the highest return. All risk measure in this thesis are calculated at 97.5% level as specified by the Basel Committee.

The marginal differences among the "No ESG Constraints," "E," "S," "G," and "ESG" portfolios imply that including or excluding ESG factors does not significantly alter the risk profile.

It is important to note that our results are specific to data, portfolios and time period we analyzed in this thesis. Performances and risk measures may not fully capture behaviour of these portfolios under different market conditions or over longer time horizons.

ESG optimization techniques we used in this study might not represent all possible ESG strategies and methods available. As such, the findings should be interpreted with an understanding of these limitations.

In the next graph we show Cumulative Returns of portfolios we analyzed in this thesis:

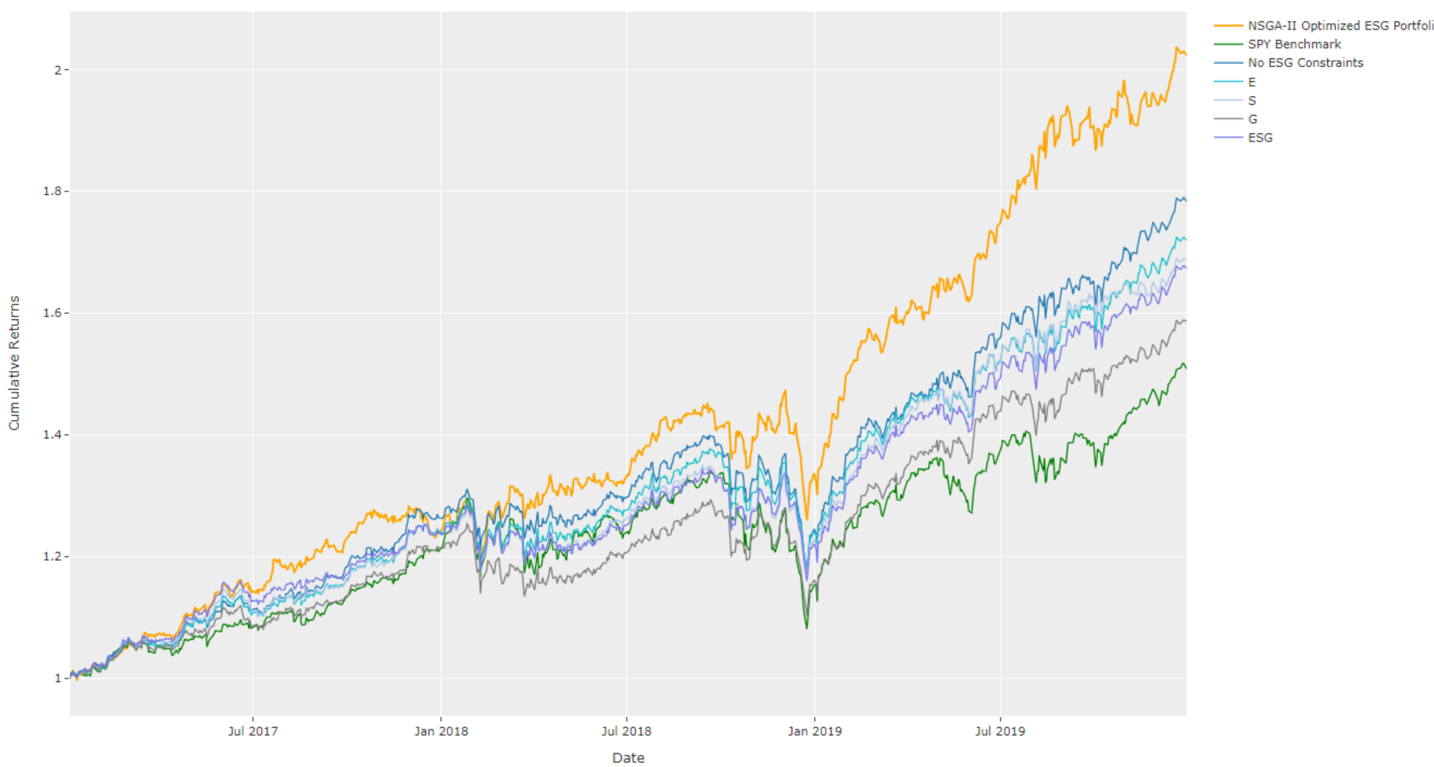

Figure 12 Cumulative returns of individual portfolios we analyzed in this thesis

4. Conclusion

ESG is both extremely important and nothing special. It's extremely important since it affects a company's long-term shareholder value, and thus is relevant to all academics and practitioners, not just those with ESG in their research interests or job title. It also affects a company's impact on wider society. This is relevant for anyone who cares about more than just financial returns, as well as for ensuring that capitalism works for all and safeguarding the public's trust in business.

But ESG is also nothing special. It shouldn't be put on a pedestal compared to other intangible assets that affect both financial and social value, such as management quality, corporate culture, and innovative capability. Like other intangibles, ESG mustn't be reduced to a set of numbers, and companies needn't be forced to report on matters that aren't value relevant. Funds that use ESG factors to guide stock selection and engagement shouldn't be lauded over those who study other value drivers, and investors in the latter deserve the same protection. We can embrace differences of opinion about a company's ESG performance just as we do about its management quality, strategic direction, or human capital management. And, perhaps most importantly, ESG needn't be politicized. Aggression and hyperbole are signs of weakness, not strength; as Karl Popper noted, “Whenever a theory appears to you as the only possible one, take this as a sign that you have neither understood the theory nor the problem which it was intended to solve.” Instead, reasonable people can disagree with each other about the factors that create value for both shareholders and stakeholders. More than that, they can learn from each other, thus enriching our knowledge on some of the biggest challenges facing business and society today. (Edmans, 2023)

In this thesis, the objective was to examine how ESG scores affect the risk profiles of portfolios we analyzed, with a focus on Expected Shortfall (ES) as a risk measure, and to compare the financial performance of portfolios that comply with ESG benchmarks against those that do not.

The theoretical contribution of this thesis is at least the following: This study has contributed to the literature examining the relationship between ESG and measures of risk in portfolio optimization, with a particular focus Expected shortfall. By analyzing the individual contributions of the Environmental (E), Social (S), and Governance (G) pillars to portfolio performance, this study provides a more detailed understanding of how each component affects financial outcomes and risks.

Most previous research has found that ESG investments generate returns equivalent to conventional equity assets while simultaneously improving diversification and reducing risk. (Andersson & Hoque, 2019) Our research has concluded that the relationship between the integration of ESG factors in selecting companies does not compromise financial performance.

Each portfolio related to ESG demonstrated better performance compared to the SPY ticker which served as market benchmark. Individual ESG constrained portfolios E, S, G, and ESG had higher cumulative and annual returns, lower volatility, and better risk-adjusted returns than the SPY benchmark. However, it is important to note that the No ESG Constraints portfolio showed better cumulative returns than the individual E, S, G, and ESG portfolios.

The NSGA-II Optimized ESG Portfolio outperformed all other portfolios, with a cumulative return of 102.38% and an annual return of 26.65%, significantly higher than both the benchmark and other ESG portfolios.

It is important to discuss some limitations that significantly impact the results, that could be addressed in subsequent research.

This study's results are only covering a small sample of S&P500 companies. Our asset universe included only 50 randomly selected companies, therefore, it is possible that the results identified in this paper are highly affected by the restricted investment universe. Producing the same tests using a different or larger dataset could provide varying results. Future studies could benefit from including a larger and more comprehensive sample universe.

The analysis is limited to only include ESG scores from a single data provider, namely Sustainalytics. This is an important limitation, as previous research show that the results differ significantly depending on which data provider is chosen (Halbritter & Dorfleitner, 2015). Recent research also suggests considerable uncertainty and inconsistency across agencies, further complicating the comparability of ESG scores. (Long et al., 2024)

We utilized ESG scores from Sustainalytics, accessed via the Yahoo Finance API using the yfinance library. Our analysis was limited to the period 2017-2019 due to significant data gaps when retrieving data for longer timeframes from the Yahoo Finance API.

Considering historical ESG data over a more extended period could enhance the accuracy and comprehensiveness of the analysis, potentially leading to more reliable results compared to shorter study periods. Therefore, we suggest that future researchers with full access to the Sustainalytics database replicate our study to obtain more precise and robust findings.

Future research could explore other optimization techniques beyond the NSGA-II algorithm, such as machine learning-based approaches or alternative evolutionary algorithms, to enhance the efficiency and effectiveness of ESG portfolio optimization. By exploring these methods, we can deepen our understanding, further improving the performance and risk profiles of ESG-optimized portfolios.

It may be interesting to mention, as noticed by (Andersson & Hoque, 2019), nowhere have we come across information that portrays ESG as a short-term investment. Quite to the contrary, the purpose behind ESG is long-term sustainability. ESG may not differentiate itself much from other equities now, but in the longterm perspective, the prospect of ESG should be more attractive than any other equity.

The integration of ESG factors into investment strategies and portfolio optimization is still evolving. The methodologies for evaluating ESG performance, the availability of consistent and comparable data, and the development of optimization techniques are all areas where progress can be made. As our understanding of ESG principles deepens and as more sophisticated tools and models are developed, it is likely that the benefits of ESG investing will become even more pronounced. Continued research in this field is essential for ESG application in portfolio management and optimization.

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