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INTEGRATION OF THE ESG CRITERIA INTO THE MODERN PORTFOLIO THEORY

An analysis on the BEL20

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Abstract

Integration of the ESG criteria into the Modern Portfolio Theory: an analysis based of the BEL20

Modern Portfolio Theory (MPT) defines an efficient frontier that represents an assortment of efficient portfolios that provide the lowest risk for a given level of expected return or the highest expected return for a defined level of risk (Markowitz, 1952). The model considers thus two parameters: (i) the expected return of rational investors and (ii) their risk aversion. Since the emergence of sustainable finance and Socially Responsible Investment (SRI), fundamentals of finance have been reconsidered by many scholars such as Pedersen, Fitzgibbons, and Pomorski (2020) or Gasser, Rammerstorfer, and Weinmayer (2017) to be more in line with investors' current needs. In this paper, we re-examine the classical model initially developed by Harry Markowitz in 1952 to incorporate the ESG score of the portfolio. In this way, it implies adding an additional decision parameter into Modern Portfolio Theory, which is the ESG score of the portfolio. Consequently, this allows us to identify a new optimal portfolio on the efficient frontier that does not solely depend on the risk (σ) and the expected return (μ). The following empirical application uses a data set from Sustainalytics conjointly with BEL20 data. By applying these models, we can observe differences arising from this new parameter in terms of efficient frontiers and efficient portfolios. Furthermore, this allows us to bring promising results for investors wishing to consider sustainable and ethical aspects of their investments. Indeed, following the research of Pedersen *et al.,* (2020), it allows us to build a *Sharpe ratio -ESG risk rating* efficient frontier able to identify portfolios achieving the best Sharpe ratio for each ESG score and an *ESG Sharpe ratio – Standard deviation* efficient frontier which derives from the *Mean-Variance and Sharpe ratio – ESG risk rating* optimizations problems. Through this study, we notice that the *SR – ESG risk rating* indicates the same tangent portfolio as the *MV* model since we optimize on the Sharpe ratio. Nevertheless, the *ESG Sharpe ratio – SD* model indicates a deteriorated tangent portfolio compared to the *MV* framework, which suggests that taking ESG scores into account in the optimization implies a degradation of the Sharpe ratio and the portfolio performance.

Keywords: portfolio optimization; Socially Responsible Investment; ESG rating score; Sharpe ratio; efficient frontier

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Glossary

ALQ	Acceptable List Questionnaire
AT	Aversion Temperature
CAL	Capital Allocation Line
CAP	Capital Allocation Plane
CAPM	Capital Asset Pricing Model
CML	Capital Market Line
CSR	Corporate Social Responsibility
CSRD	Corporate Sustainability Reporting Directive
DCF	Discounted Cash Flow
DJIA	Dow Jones Industrial Average
E	Environmental
EC	European Commission
EMH	Efficient Market Hypothesis
ETF	Exchange Traded Fund
ESG	Environmental, Social and Governance
ESG SR-SD	Environmental Social Governance Sharpe Ratio – Standard Deviation
EU	European Union
FCF	Free Cash Flow
G	Governance
GBL	Groupe Bruxelles Lambert
GPSM	General Mean-Variance Portfolio Selection Model
IPCC	Intergovernmental Panel on Climate Change
KBC	KredietBank and CERA
MASD	Mean-Absolute Semi-Deviation
MEI	Material Environmental Issue
MiFID	Markets in Financial Instruments Directive
MOEA	Multi-Objective Evolutionary Algorithm
MPT	Modern Portfolio Theory
MRF	Manageable Risk Factor
MSCI	Morgan Stanley Capital International
MV	Mean Variance
MV-ESG	Mean Variance – Environmental Social Governance
MVL	Mean Variance Leverage
MVS	Mean Variance Skewness
NFRD	Non-Financial Reporting Disclosure
NFR	Non-Financial Reporting
NSGA	Non-Domination Sorting Genetic Algorithm
RDD	Regression Discontinuity Design
S	Social
SD	Standard deviation
S&P	Standard & Poor’s
SFDR	Sustainable Finance Disclosure Regulation
SML	Security Market Line
SR	Sharpe Ratio
SR-ESG	Sharpe Ratio – Environmental Social Governance
SRI	Sustainable Responsible Investment
TR	Taxonomy Regulation
TV	Terminal Value

VAR	Value At Risk
WACC	Weighted Average Cost of Capital
WDP	Warehouse De Pauw

Additional glossary

In the scope of this thesis, the following terms designate the Modern Portfolio Theory: classic theory, standard theory, Harry Markowitz's model and Mean-Variance model.

We have also used synonyms for the different models developed in the empirical part according to their order. The first optimization method corresponds to the Modern Portfolio Theory. The second optimization refers to the Sharpe ratio - ESG risk rating optimization. Finally, the third optimization represents the ESG Sharpe ratio - Standard deviation optimization method.

General introduction

Political discussions to address global warming started in the 1990s and since then, the situation has only gotten worse. The latest Intergovernmental Panel on Climate Change (IPCC) report reveals alarming figures. For example, governments plan to produce twice as much fossil fuel by 2030 as needed to limit global warming to 1.5°C (Greenpeace, 2022). We all have felt completely powerless when it comes to climate change. But fighting global warming is everyone's interest and business and a series of small actions can achieve big changes. Finance has a part to play too in our efforts to address global warming.

The association between the words 'finance' and 'sustainability' may appear paradoxical at first sight. For some, there is a contradiction between finance, the field in which people seek unreasonable profits, and sustainability. Sustainable finance may look like greenwashing to some. Nevertheless, ESG investing gains in popularity (LaBella, Sullivan, Russel, and Novikov, 2019). According to Bloomberg (2022), ESG assets are expected to exceed $50 billion by 2035. A substantial increase in the coming years.

One way to create interaction between finance and sustainability is to behave more responsibly as investors. This would allow capital to be directed towards more sustainable, and environmentally conscious companies with ethical practices. There are many investment strategies to do this (Eurosif, 2022), but there are still many tools in finance that need to be improved and updated.

In portfolio management, asset owners and managers experience a growing momentum towards sustainable finance. Nevertheless, there is very little guidance on how to integrate ESG criteria into portfolio management and there is also much debate between academics and practitioners regarding the impact of ESG securities' performance (Pedersen *et al.*, 2020). The objective of this thesis is to analyze how ESG has been integrated before in portfolio management and to propose an "improvement" to the most widely used optimization tool in this area.

PART 1 – LITERATURE REVIEW

Introduction to the literature review

This thesis is organized into two major sections. The first part focuses on the literature review while the second part addresses the empirical section of the thesis.

The purpose of the literature review is to introduce topics and concepts that are relevant to the research question and that will be useful for analyzing the empirical part.

The theme of this thesis is the integration of the ESG criteria into the optimization model as proposed by Modern Portfolio Theory (MPT) initially developed by Harry Markowitz in 1952.

The objective of the following chapters is to review the literature to understand what studies have been done before on the matter and to propose a straightforward portfolio optimization tool able to consider ESG scores in addition to return and risk.

The literature review is divided into three main chapters. First, we will discuss all the key concepts of Modern Portfolio Theory that will be useful in the empirical part. We will also elaborate on Socially Responsible Investment (SRI) and its development. Finally, we will investigate the existing literature that has previously proposed to revisit optimization models derived from Modern Portfolio Theory.

1 Chapter: Modern Portfolio Theory

Portfolio management is an area in finance in which two major theories are used. On the one hand, there is the Capital Asset Pricing Model (CAPM) which was introduced by William Sharpe (1964) and by John Lintner (1965). On the other hand, there is the Modern Portfolio Theory (MPT) which was initially developed by Harry Markowitz (1952, 1959). "The portfolio selection may be divided into two stages: the analysis of available assets and the combination of selected assets into a portfolio. The Modern Portfolio Theory deals with the second stage" (Neves, Da Silva, and Vasconcellos, 2017, p.18).

1.1 Key concepts of Modern Portfolio Theory

1.1.1 Premises of Modern Portfolio Theory

Harry Markowitz (1952, 1959) is at the origin of Modern Portfolio Theory. The objective of this model is to construct portfolios of securities that consider two parameters: the expected return of investors and their risk aversion (**cf. infra p.8**). Markowitz (1952, 1959) expresses return through the expected return (μ) and risk through the standard deviation (σ) which flows from the variance (σ^2) (**cf. infra p.5**). Modern Portfolio Theory's main objective is to solve the asset allocation problem by proposing an optimization problem capable of minimizing risk for a certain level of return. The underlying idea behind Modern Portfolio Theory is diversification (**APPENDIX II: Diversification**). By introducing assets with low correlation (**cf. infra p.7**), it is possible to achieve a higher return for reduced risk.

Through his framework, Markowitz (1952, 1959) was able to model returns as random variables by using their variance as a risk measure. He also contributed to the development of a mathematical formula for computing the expected return and the risk of a portfolio based on the expected returns and co-variances of its constituent securities. Finally, his work introduced the notion of portfolio optimization and the existence of efficient portfolios (Lhabitat, 2017).

1.1.2 Return

The return is the overall gain or loss that an investor has achieved on an investment (Fama, 1968).

$$R_i = \frac{S_{i,T=1} - S_{i,T=0}}{S_{i,T=0}} \tag{1.1}$$

Where

$S_{i,T}$ *is the price of asset i at time T*

The portfolio return is given by the following formula:

$$R_P = w_1R_1 + w_2R_2 + \cdots + w_NR_N = \sum_{i=1}^{N} w_iR_i \tag{1.2}$$

Where

R_P *is a random variable*

w is the weight invested in each security

1.1.3 Risk

As mentioned hereinabove (**cf. supra p.4**), the total risk of a portfolio is given by the variance of the portfolio returns:

$$\sigma_p^2 = \mathrm{VAR_p} = \sum_{j=1}^{N}\sum_{k=1}^{N} \mathrm{x_j x_k Cov}(\mathrm{R_j}, \mathrm{R_k}) \tag{1.3}$$

$$\sigma_p^2 = \mathrm{Cov}(\mathrm{R_j}, \mathrm{R_k}) = \frac{1}{\mathrm{T}}\sum_{t=1}^{\mathrm{T}}\left[(\mathrm{R_{j,t}} - \mathrm{E_j})(\mathrm{R_{k,t}} - \mathrm{E_k})\right] = \rho_{\mathrm{jk}}\ \sigma_{\mathrm{j}}\ \sigma_{\mathrm{k}} \tag{1.4}$$

Where

ρ_{jk} *is the correlation between securities' returns j and k*

σ_j *is the standard deviation of security j*

σ_k *is the standard deviation of security k*

One of the most important aspects of Harry Markowitz's work is that he demonstrates that it is not the risk of a single stock that is relevant to an investor, but rather the contribution of that stock to the entire variance of the portfolio. This is the concept of covariance in the portfolio (Rubinstein, 2002). Hence, Rubinstein (2002) explains that when an investor wants to keep a stock in his portfolio, there is no point in comparing the return and variance of this stock with the others, but rather to look at what the impact would be of keeping this stock in relation to the other stocks preserved in the portfolio.

In Modern Portfolio Theory, risk is more specifically characterized by assets' volatility. In other words, it is the standard deviation from the average return (Markowitz and Todd, 2000). The latter "is the statistical measure of market volatility, measuring how widely prices are dispersed from the average price" (Fidelity Investments, 2022, para.1). The standard deviation is the square root of the variance:

$$\sigma_p = \sqrt{\sigma_p^2} \tag{1.5}$$

1.1.4 Correlation and Modern Portfolio Theory

"Correlation refers to the degree to which investments within a portfolio share similar risk and return characteristics. A portfolio bearing assets that are highly correlated is less diversified. As a result, high correlation is associated with greater risk in the form of volatility" (Court Investment Services, 2017, para. 1). Correlation between assets is expressed by a coefficient between -1.0 and 1.0. The closer this number is to 1.0, the stronger the relationship between the two assets. By contrast, if the number is close to 0.0 or even negative, the two assets will behave more independently of each other (Morningstar, 2014). Following Modern Portfolio Theory, the most suitable correlation is 0 or around 0 between securities as assets having a correlation of 1.0 will similarly move and thus alter the diversification process.

$$\rho_{ij} = \frac{Cov(r_i, r_j)}{\sigma_i \, \sigma_j} \tag{1.6}$$

$Where$

ρ_{ij} $is\ the\ correlation\ between\ security\ i\ and\ security\ j$

$Cov\ (r_i, r_j)$ *is the covariance of return of security i and security j*

σ_i $is\ the\ standard\ deviation\ of\ security\ i$

σ_j $is\ the\ standard\ deviation\ of\ security\ j$

1.1.5 Mean-Variance analysis

Mean-Variance analysis is part of Modern Portfolio Theory and is represented by an optimization problem to find the optimal portfolio. Markowitz proposes to "minimize variance of R_P subject to a lower bound on the expected return of R_P" (Lassance, 2021, p.17).

$$min_{w \in W}\ \sigma_P^2\ subject\ to\ \mu_P \geq \mu_0 \tag{1.7}$$

$Where$

$W\ is\ a\ set\ of\ constraint\ regarding\ the\ portfolio\ weight,$

$including\ at\ least\ \sum_{i=1}^{N} w_i = 1$

$\mu_P\ is\ the\ expected\ value\ of\ R_P$, E $(R_P), with\ \mu_P = w'\mu$

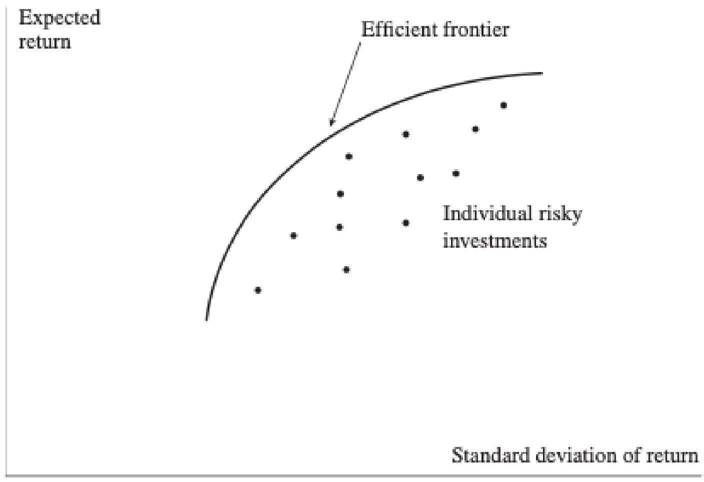
1.1.6 Efficient Frontier

"An efficient frontier is a set of investment portfolios that are expected to provide the highest returns at a given level of risk. A portfolio is said to be efficient if there is no other portfolio that offers higher returns for a lower or equal amount of risk. Where portfolios are located on the efficient frontier depends on the investor's degree of risk tolerance" (Corporate Finance Institute, 2022). This means that every possible risk-reward relationship can be plotted on a graph. For each level of return, there is an existing portfolio that minimizes the risk and the same applies for each level of return.

The universe that composes the efficient frontier only includes risky assets (stocks). The abscise represents the total risk and the ordinate is the expected return.

Figure **1.1** illustrates the efficient frontier where all individual portfolios below the efficient frontier are inefficient as it is possible to achieve a higher return for the same risk load. Or it is also feasible to achieve the same return for a lower risk load. All points on the curve represent efficient portfolios. Among these, there is the tangent portfolio, i.e., the one with the highest Sharpe ratio.

Figure 1.1: Harry Markowitz's model



Source: Hull, J. (2018). Risk Management and Financial Institutions (5th Edition). United States of America: Wiley Finance Series

1.2 Utility function

Neves *et al.,* (2017) explain in their article *Maximization of utility and portfolio selection* that the utility function is widely used in Modern Portfolio Theory to identify the optimal portfolio corresponding to an investor's expected return and risk aversion. The authors begin by asserting that the utility function is the foundation of the theory of choice under uncertainty. Von Neumann and Morgenstern (1947) have widely contributed to the elaboration of the Theorem of the Utility Function. The latter allows a level of satisfaction to be matched to a level of wealth. A typical utility function demonstrates that more wealth is always preferable to less wealth. At first, this function is increasing. This means that more wealth will always be better than less wealth. Then, this function becomes concave. This means that the utility function has a decreasing marginal utility. The more the level of wealth increases, the fewer satisfaction investors will get from it. According to Von Neumann and Morgenstern (1947), a rational agent will try to maximize its expected utility.

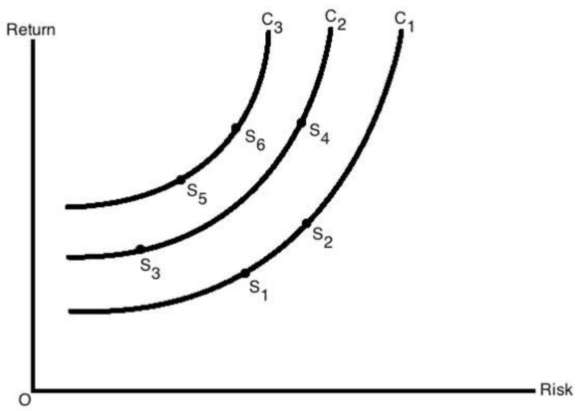
Modern Portfolio Theory is also an optimization problem to be solved since its objective is to minimize the risk load for a given return. If we investigate more in detail, the solution to this optimization problem is the maximization of the underlying expected utility of the investor (Neves *et al.*, 2017) (**cf. supra p.7**).

In practice, once the universe of assets is defined and the efficient frontier (**cf. supra p.8**) has been determined, it is necessary to identify the optimal portfolio for a specific investor. To do so, Modern Portfolio Theory selects a portfolio based on the investor's indifference curves (Formula **1.8**, Figure **1.2**) and the efficient frontier.

$$\mathrm{U} = \mathrm{E(r)} - \frac{1}{2}\mathrm{A}\sigma^2 \tag{1.8}$$

$Where$
$U\ is\ the\ the\ utility\ of\ an\ investment$
$E(r) is\ the\ expected\ return$
$A\ is\ the\ measure\ of\ risk\ tolerance\ or\ risk\ aversion$
$\sigma^2\ is\ the\ variance\ or\ risk$

Figure 1.2: Indifference curves



Source: P2R Academy. (2022). Indifference map. Retrieved the 16th of March 2022 from https://www.pace2race.com/lessons/indifference-curve/indifference-map/

1.3 Assumptions of Modern Portfolio Theory

Harry Markowitz's model relies on various behavioral assumptions (Mangram, 2013; Kim and Francis, 2013):

- Investors are rational. This means that they try to maximize their return while minimizing risk.
- Investors accept additional risk load only if it results in a higher return.
- Investors have access to relevant information to make their investment decisions.
- Investors can borrow or lend unlimited amounts of money at risk-free interest rates.
- Markets are efficient.
- Markets are not subject to transaction costs or taxes.
- Investors can select securities whose performance is independent of the overall performance of the investment portfolio.

1.4 Sharpe Ratio

In portfolio management, there are a variety of performance indicators. The Sharpe ratio is one of the most used. The latter, also called the reward-to-variability ratio, was developed by William Sharpe in 1966. Its purpose is to measure volatility-adjusted performance (Israelsen, 2005). Concretely, the ratio is the average return obtained in excess of the risk-free rate per unit of total risk (Zakamouline and Koekebakker, 2009).

$$\text{Sharpe ratio} = \frac{\mathrm{R_p} - \mathrm{R_f}}{\sigma_\mathrm{p}} \tag{1.9}$$

Where

R_p *is the return of the portfolio*

R_f *is the risk − free rate*

σ_p *is the standard deviation of the portfolio's excess return*

The result of the Sharpe ratio can be less than, equal to, or greater than 0. If the ratio is negative, it implies that the portfolio of securities performs poorer than a risk-free investment while taking a greater risk. If the result ranges between 0 and 1.0, it means that the excess return over the risk-free rate is lower than the risk taken. Finally, if the ratio is greater than 1.0, this indicates that the portfolio delivers a superior return for its level of volatility (McLeod and Van Vuuren, 2004).

When plotting the Capital Allocation Line (CAL) (**APPENDIX V: Capital Allocation Line**) against the efficient frontier, the intersection is the tangent portfolio, i.e., the one with the highest Sharpe ratio.

2 Chapter: Socially Responsible Investment

The rise of sustainable finance in recent years has led to an increasing interest in the matter from both practitioners and academics. The purpose of this chapter is to discuss the evolution of the role of sustainable finance for investors as well as for institutions. One of the most widely used providers of ESG data will also be touched upon in this chapter.

2.1 Historical development

The origins of Socially Responsible Investment (SRI) go back to the beginning of the 20th century. At first, religious convictions were one the most influential factor in prohibiting certain investments. For example, some Islamic communities have chosen to avoid investing in sectors such as those involved in pork production. Then, around the 1950s, ethical and social convictions began taking over as influential factors excluding certain investments. It should also be highlighted that historical events and movements have had a considerable impact on investment decisions throughout time. For instance, the Vietnam War in the 1970s, which was highly contested by the Americans, had the effect of precluding investments in weapons (Von Rennenboog, Ter Horst, Zhang, 2005; Wallis and Klein, 2015).

As of recently, climate change has become an additional factor that can affect investors' decisions. Indeed, Von Wallis and Klein (2015) explain that climate emergency has a consequent effect on investment decisions. Indeed, it can be perceived that some believe it necessary to favor sectors that are active in energy transition while others decide to ban investments in polluting sectors. This change in behavior in investment decisions has been summarized and illustrated by Von Wallis and Klein (2015) as follows: "Investment decisions initially followed a simple triangle, covering liquidity, risk, and return. Nowadays, an increasing number of investors use the magical square: liquidity, risk, return, and sustainability" (Von Wallis and Klein, 2015, p.63).

2.2 What is Socially Responsible Investment?

Eursosif (2022) defines Socially Responsible Investment as "a long-term oriented investment approach that integrates Environmental, Social & Governance (ESG) factors in the research, analysis, and selection process of securities within an investment portfolio. It combines fundamental analysis and engagement with an evaluation of ESG factors in order to better capture long-term returns for investors, and to benefit society by influencing the behaviour of companies" (Eurosif, 2022, para.1).

According to Renneboog, *et al.*, (2008), Socially Responsible Investment thus applies filters to exclude or select some investments. These filters may be implemented based on ecological, social, corporate governance, ethical or moral criteria. These considerations in the investment decision process are therefore different from the more conventional types of investments and result in several strategies (**APPENDIX VIII: Socially Responsible Investment strategies**).

2.3 Environmental, Social, and Governance considerations

Robeco (2022) defines environmental, social, and governance factors as metrics to evaluate companies. A brief overview of each factor will be provided so that their role in the investment decision process can be perceived.

The environmental factor focuses on the impact of a company on its surrounding environment or climate change (Robeco, 2022). It considers every aspect of a company's activity on the environment and whether the impact it has is positive or negative. For instance, the aspects considered include renewable energy, greenhouse gas emissions, and water use (Eurosif, 2022).

Then, the social factor is closely linked to the community aspects. It aims at taking into consideration health improvement, education, or work conditions. Its analysis is mainly centered on human rights, the development of social rights, or the employee training policy for example (Eurosif, 2022).

Finally, the governance factor primarily addresses the quality of the company's management, the diversity within the company, the firm's corporate culture, and the respect for shareholder's rights (Eurosif, 2022; Robeco, 2022).

2.4 SRI investors

2.4.1 Additional factors in decision making

Since the 1950s, investors have been defined as rational. This is also one of the main assumptions of Modern Portfolio Theory (**cf. supra p.10**). Rationality amongst investors implies that only risk and return are considered when making an investment decision.

This concept has been prevalent in finance for decades. Yet, according to Beal, Goyen, and Philips (2005), there is a growing body of literature acknowledging that investors do not always behave as described by classical theories. They are subject to many cognitive biases and heuristics. Amongst many others, Lease, Lewellen, and Schlarbaum (1976) have found through their research that investors tend to make investment decisions that are aligned with their philosophy and that are linked to individual circumstances. This suggests that individual preferences may interfere with the free flow of capital and the achievement of a coherent risk-return tradeoff between securities (Bean *et al.*, 2005).

In another study, Nagy and Obenberger (1994) demonstrated on a sample of thirty-four investors that seven factors influenced investors in their choices. It can thus be noted that this goes far beyond the risk and return factors initially considered. In addition, they noted that more than half of investors significantly considered non-maximizing criteria such as their feelings for firm's products and services. This is another illustration of the relevance of non-financial aspects when making investment decisions.

2.4.2 Rise of SRI investors

Given the above, we can therefore conclude that investors consider various factors and do not behave rationally as originally defined in the Modern Portfolio Theory. Among these factors, we notably find the relevance of ethical values.

Geczy, Stambaugh, and Levin (2003) believe that private investors are willing to invest in projects that match their personal values. For example, Renneboog *et al.,* (2008) explain that investors take ethical, environmental, social, and governance dimensions into consideration, as good scores in those areas are signals of good managerial quality. In their opinion, investors find utility "by doing good" and not by solely concentrating on risk and return (**cf. supra p.8**).

As Socially Responsible Investment is becoming an increasingly popular topic in finance, new studies are being conducted to investigate investors' behavior towards this financial field. For example, Huang and Weng (2020) and Ammann, Bauer, Fischer, and Müller (2019) demonstrated that mutual funds with a higher sustainability rating or a label are more attractive to inflows compared to less sustainable funds. This is also what the research paper *the power of ESG transparency: the effect of the new SFDR sustainability labels on mutual funds and individual investors,* written by Becker, Martin, and Walter (2022), attempted to investigate. The authors demonstrated the effect of the Sustainable Finance Disclosure Regulation (SFDR) (**cf. infra p.20**) to direct capital to sustainable investments. In some respects, these studies illustrate the growing popularity of ESG funds among investors and the genuine interest emerging for sustainable finance.

This interest in Socially Responsible Investment also challenges some important concepts such as performance. Some believe that there is a need to revise the notion of financial performance in a new and different way (Mortier, 2021). Renneboog *et al.*, (2008) believe that it is necessary to broaden its scope and to recognize that non-financial value also derives from investments. For example, performance should also consider social change, or ecological achievements of the investment could be added to the financial performance (Reeder and Colantonio, 2013).

Although the main motivation behind this approach appears to be social and ethical, it is also likely that a financial incentive contributes to it too. In addition to generating social performance, there may be a long-term financial gain for the investor in considering ESG factors. According to Von Wallis and Klein (2015), the increase in Socially Responsible Investment interest among private investors over the past decade may have been driven by the fact that SRI investments can provide better financial returns than conventional investments over the long-term. It is also believed that it enables investors to avoid high costs during corporate social crises or environmental catastrophes (Renneboog *et al.,* 2008). We will discuss this topic later in section 2.5 (**cf. infra p.15**).

We can thus conclude that there are three main motivations driving individuals to consider ethical investments. These are the following: superior financial returns, non-wealth returns, and contribution to social change (Beal et *al.*, 2005).

2.5 Socially Responsible Investment and Financial Performance

The notion of possible financial sacrifice in Socially Responsible Investment has provided fertile soil for research (Jones, van der Laan, Frost, and Loftus, 2008). Indeed, one of the main questions in sustainable finance is whether ethical and sustainable practices would enable companies and investors to achieve better financial performance in the long run. There is no real consensus on the matter since research methodologies, performance indicators, time frames, and ethical factors differ from one study to another. On the one hand, some academics and practitioners, such as Cornell (2020), believe that there is a tradeoff between sustainable business practices and financial performance. According to them, the additional costs of carrying out those practices are higher than the gains. On the other hand, others are convinced that sustainable practices enable companies to achieve better financial results because they drastically reduce the risk they encounter. Hussain, Rigoni, and Cavezzali (2015) establish that there are three main schools of thought on the matter: the traditionalist view, the revisionist view, and the last stream which combines both the traditionalist and the revisionist view.

Cornell (2020) recognizes the benefits of Socially Responsible Investment but maintains a traditional approach to the subject. Indeed, he explains that companies with a good ESG score will have access to a lower cost of capital and will be better protected in case of climate shocks or new regulations. However, he points out that this comes at a cost to investors. He, therefore, dug deeper into the drivers of the risk premium and behavioral biases and their relationship with ESG characteristics, investment risk, and expected returns. He concluded by stating that ESG-oriented investors have a high social impact but are likely to be disappointed in terms of returns.

Conversely, Flammer (2015) supports the revisionist claim. She studied whether an improved Corporate Social Responsibility (CSR) could lead to superior financial performance. To capture exogenous variation in CSR, she used the passage of shareholder proposals on CSR that are approved or rejected by a limited number of votes. Flammer (2015) applied a Regression Discontinuity Design (RDD) methodology and found that the implementation of aligned CSR proposals resulted in a significant increase in shareholder value of 1.77%.

Likewise, from a more revisionist perspective, Morningstar (2021) investigated the impact of ESG factors on share price growth. Morningstar (2021) explains that this relationship is difficult to establish due to the latest events that have taken place in recent years such as Brexit and Covid-19. Nevertheless, Morningstar (2021) points out in an interview with Matthew Jennings, investment director at Fidelity, that companies with a low ESG risk score “avoid higher regulatory costs, litigation, brand erosion, and stranded assets, while strong governance protects profits” (Morningstar, 2021, para. 9). Morningstar (2021) adds that some past work has suggested that the inclusion of ESG factors tends to have a beneficial effect on a company's financial performance. Moreover, stocks with low ESG risk tend to do somewhat better in weak markets or during times of social and economic crisis, while some may underperform in robust financial markets.

Furthermore, according to the NYU Stern (2020), environmentally conscious firms who try to reduce their carbon footprint are more likely to have better financial performance in the future as this would allow them to reduce the risk. Cheema-Fow, Laperla, Serafeim, Turkington, and Wang (2019) investigated decarbonization agents and discovered that various decarbonization approaches can produce different risk-adjusted returns. Specifically, they found that the most aggressive carbon reduction strategies outperformed. They evaluated 736 US public companies in two cities from 2005 to 2015 and discovered that adopting a long position on carbon-efficient companies and a short position on carbon-inefficient companies could deliver an annual abnormal return of between 3.5% and 5.4%. NUY Stern (2020) also supports that firms with sustainable initiatives appear to drive financial performance as they have better management and are more innovative.

In addition to that, Morningstar (2021) and Xiong (2021) argued that a low ESG risk rating translates into a lower cost of capital, lower interest rates for corporate bonds, and higher share prices as there is less risk of failure and future earnings are expected to be higher.

Finally, if we focus on the relationship between ESG and dividends, a recent report by Fidelity International revealed a correlation between dividend growth and ESG performance. The report found that, on average, firms with a strong sustainability rating have the highest levels of historical dividend growth, at more than 5% over the past five years, while firms with a poor rating have the lowest average levels of dividend growth (Business Times, 2021). For instance, oil companies are gradually beginning to pay out less and less in dividends, as they are making major investments to become greener (Morningstar, 2021).

The literature does not fully find a consensus about the impact of Socially Responsible Investment on corporate financial performance. As aforementioned (**cf. supra p.15**), this is mainly due to the different methodologies and varying criteria considered in studies (Gasser *et al.*, 2017). It should also be highlighted that there was no evidence of improved economic performance for companies with better social performance, but neither was there any indication of deterioration in economic performance (Hickman, Teets, and Kohls, 1999).

Finally, it is worth mentioning that some academics believe that the debate is not whether ESG leads to better financial performance, but rather when it is advantageous. This is what King and Lenox (2001) have discussed in their article *Does it pay to be green?* They observed that many academics were arguing whether there was a tradeoff between environmental and financial performances. They suggested that these studies often lacked longitudinal data and that this needs to be better tested. Amongst other findings, they concluded that the real question was not: does it pay to be green, but rather, when does it pay to be green?

2.6 European regulations and Socially Responsible Investment

The European Union (EU) has decided to put sustainability at the core of its objectives, notably through the implementation of the European Commission's (EC's) Action Plan on Sustainable Finance. The latest includes a set of 4 legislative measures on the following topics: development of the taxonomy, improved sustainable advisory for clients, target of low-carbon benchmarks, and report on investor's duties and disclosures. Through this, the EU expects to meet three objectives. First, it hopes to redirect capital to projects that will achieve sustainable growth. Second, it expects to manage financial risks arising from climate change, environmental deterioration, and social issues. Third, the EU hopes to increase transparency and long-termism in financial and economic activity (Green Finance Platform, 2018).

2.6.1 Markets in Financial Instruments Directive (MiFID)

"The Markets in Financial Instruments Directive (MiFID) is a European directive on investments. The directive has three objectives:

1. Protecting investors and safeguarding the integrity of financial markets.
2. Promoting fair, transparent, efficient, and integrated financial markets.

3. Further harmonizing European stock trading and the investment market" (FSMA, 2022, para.1).

According to the European Union (2020), the current directive 2014/65/EU (MiFID II) framework covers two main areas for investment firms in practice.

First, any investment firm that delivers financial instruments intended to be distributed to clients is required to maintain, apply, and review an approval process for each financial instrument before its marketing or distribution.

Second, the investment firm should ensure that financial products it offers to its clients correspond to their needs. Currently, MiFID II requires professionals providing financial advice and discretionary portfolio management to take into account their client's financial objectives, risk profiles, and financial education (Deloitte, 2020). Yet, one important aspect is not included in the information that portfolio managers or financial institutions must collect on their clients. This is their ESG preferences.

Initially, the European Union omitted to create a section in MiFID II that would accentuate the sustainable dimension of investing (European Union, 2020). This is the reason why a new directive (EU) 2017/593 was introduced so as to integrate sustainability considerations within the investment process. The latter reinforces the first directive 2014/65/EU and demonstrates the Commission's willingness to embrace a transition to a greener and more sustainable EU. Nevertheless, there is still a lot of work to be done regarding the implementation of investor's sustainable preferences questionnaire as previously mentioned. For the time being, financial institutions such as banks are required to interpret the legislation without clear guidelines and make their own arrangements for the implementation of this new part of MiFID II (Michaël Van Den Spiegel, 2022) (**APPENDIX XV: Semi-directed interview guide - Michaël Van den Spiegel**).

2.6.2 Sustainable Finance Disclosure Regulation (SFDR)

"The European Regulation (EU) 2019/2088 on sustainability disclosure in the financial services sector, or SFDR Regulation, imposes transparency rules on financial market participants and financial advisors in the EU regarding the integration of sustainability risks and the consideration of negative sustainability impacts in their investment and advisory processes" (Banque Internationale à Luxembourg, 2022, para.1).

SFDR plays an important part in the EU's sustainable development agenda. Its purpose is to increase transparency on sustainability for financial institutions but also for market participants and therefore avoid greenwashing (Pwc, 2022).

The SFDR will be applied on two distinct levels (**APPENDIX X: Sustainable Finance Disclosure Regulation**):

1. Entity-level: firms will have to disclose information on their policy in terms of sustainability risks that is applied when making investment decisions.
2. Product-level: entities will have to disclose information with regards to the sustainability dimension of the product. For example, firms will have to report how sustainability risks are integrated and what could be the impact of these risks on the return of the product.

2.6.3 Non-Financial Reporting Directive (NFRD) and Corporate Sustainability Reporting Directive (CSRD)

NFRD came into force in 2017. Its scope targets mainly large, listed companies and public interest companies with more than 500 employees. The European Union (EU) Directive 2104/95/EU on non-financial disclosure and diversity therefore requires companies to disclose non-financial information about their corporate policy, anti-corruption measures, climate policy, gender equality, and more (La Torre, Sabelfeld, Blomkvist and Dumay, 2020). The directive's initial purpose is to enhance confidence between investors and stakeholders. In addition, this directive aims to improve "environmental, social and governance reporting in the European States by establishing some minimal legal requirements for non-financial reporting (NFR) and making it mandatory" (La Torre *et al.,* 2020, p. 702). Finally, by imposing the Non-Financial Reporting Directive (NFRD), European Union hopes to positively influence the corporate social responsibility of companies and encourage them to implement better sustainable practices.

According to the European Parliament (2022), the Commission submitted its proposal for a Directive on Corporate Sustainability Reporting (CSRD) in April 2021. CSRD aims to review and reinforce the existing set of rules introduced by the NFRD and to, over time, bring sustainability reporting to the same level as financial reporting. Companies will be required to provide an assessment of the impact of sustainability issues on their operations and the impact of their activities on the environment. In addition, the Commission proposes to extend the scope of the NFRD to a wider panel. From now on, the number of companies that will have to publish their non-financial reports will increase from 11,000 to almost 50,000 (European Parliament, 2022).

2.6.4 European Taxonomy Regulation (TR)

The European taxonomy was created to define in a standardized framework what "sustainable" means for the different member states (European Commission, 2022). Its objective is to provide companies, investors, and stakeholders with the appropriate criteria and definitions clarifying which economic activities fall within the scope of sustainability. Through this tool, the Commission hopes to improve transparency for investors, reduce greenwashing from companies, and redirect financing to projects and companies considered to be genuinely committed to the climate.

The European taxonomy came into force in June 2020 and establishes a list of criteria that economic operations must reach to be considered environmentally sustainable (European Commission, 2022).

It can therefore be seen that the different legislations listed above are intertwined. Indeed, first, the European taxonomy determines a common notion of activities that can be considered sustainable. Then, the CSRD, which is based on the NFRD, makes the reporting of non-financial information by companies more transparent and complete. The SFDR thus requires financial institutions to disclose more information about the sustainability and ethical policies they have in place within their organization and the sustainability of their products. And, finally, MiFID II, taking clients' sustainable preferences into account, will rely on the taxonomy, the SFDR, the NFRD, and the CSRD to determine the investment universe that will correspond to clients.

All of the aforementioned regulatory safeguards set by the EU suggest that there will be an important shift in sustainable investment within the upcoming years.

Figure 2.1: Taxonomy, NFRD, CSRD, SFDR, and MiFID

Business	**Product**	**Service Provider**	**Investor**
▪ Taxonomy Regulation (TR) ▪ Non-Financial Reporting Directive (NFRD) ▪ Corporate Sustainability Reporting Directive (CSRD)	▪ Sustainable Finance Disclosure Regulation (SFDR)	• Sustainable Finance Disclosure Regulation (SFDR) • Markets in Financial Instruments Directive (MiFID)	

staggered effective dates

Source: Dumas, C. (2021). Ethics in Finance. Slides: ICHEC Brussels Management School. Brussels.

2.7 Providers

As highlighted previously (**cf. supra p.11**), the momentum for ESG is only increasing. In 2019, it was estimated that more than $30 trillion of assets under management were invested while considering ESG data (LaBella *et al.*, 2019). It is therefore an essential feature of portfolio management. Yet, companies' ESG analysis is a time-consuming task and requires dedicated analysts specialized in the matter. This is the reason why rating agencies aim to provide ESG scores to a universe of companies. There are several rating agencies but the most famous are Sustainalytics, MSCI, RobecoSAM, and Asset4.

There is no doubt that these rating agencies play, and will keep on playing, a key role in financial markets as they have a lot of influence (Escrig-Olmedo, Fernàndez-Izquierdo, Ferrero-Ferrero, Revera-Lirio and Munoz-Torres, 2019). In fact, they play an essential role because the potential of assets under management is considerable, but also because major players are actively acquiring rating agencies, and finally because regulation is flowing in their direction (Berg, Koelbel, and Rigobon, 2020).

Due to their large number, there are many methodologies for assigning an ESG score to companies. In fact, even though it is strongly encouraged by organizations such as the Global Reporting Initiative and the Task Force on Climate-related Financial Disclosures (LaBella *et al.*, 2019), there is no standardized methodology in this area yet. As a result, there are many discrepancies and variations between scores assigned by rating agencies to the same companies. This is because they do not consider the same factors for the E, S, and G categories. Moreover, they do not assign the same weight and significance to the various factors either. This is the reason why LaBella *et al.*, (2019) explain in their article *The devil is in the details: the divergence in ESG data and implications for responsible investing* that it is important to encourage investors to think critically when using these ratings. It is also worth understanding how the score is computed and seeking additional information.

2.7.1 Sustainalytics

In this chapter, we will mainly concentrate on Sustainalytics as a provider which will be used in the empirical part for determining ESG scores.

Sustainalytics is part of Morningstar Company. It is an independent firm that is involved in the ESG and corporate governance ratings research and ratings. These ratings enable companies and investors to identify ESG issues that pose a financial-material risk (Sustainalytics, 2022).

2.7.2 Sustainalytics' methodology

First and foremost, the core building block of Sustainalytic's ESG risk rating is the Material ESG Issue (MEI) notion. It is defined and assessed by the following elements.

Sustainalytics (2018) defines an ESG risk as a material risk that can have an impact on the financial value of the company and therefore on the risk of the investment and its return. A material risk is also characterized by the fact that its presence or absence might influence the investor's decisions.

If the identified factors are ESG material, they must be sufficiently relevant in terms of ESG impact and have a substantial influence on the drivers of a discounted cash flow (DCF) model. Consequently, factors could either have an impact on its ability to generate free cash flows (FCF) in the future or it could influence the systematic risk of the company and thus have an impact on the weighted cost of capital (WACC) or on the terminal value (TV) of the company.

Once an ESG risk has been assessed as material and as having an impact on the financial value of the company, it is then necessary to add the first dimension. This relates to exposure. "Another way to think of exposure is as a company's sensitivity or vulnerability to ESG risks. Negligible exposure suggests that the issue is of little material importance to a company; higher exposure suggests that the issue is material" (Sustainalytics, 2018, p.20). The definition of the exposure score is determined in three steps. In the first place, a comprehensive and detailed analysis of the industry in which the company operates is carried out. Then, Sustainalytics (2018) assigns a straightforward multiplier (β) at the individual company level, which captures the company's specific deviations from the sub-sector norm for all issues identified as material to that sub-sector. For example, the beta takes into account the location of the company as this can have a significant impact (i.e., in terms of resource scarcity). The beta can range between 0 and 10. The last step consists in arriving at the final exposure score. To do so, analysts combine the first two steps. In practice, the exposure score that has been defined is multiplied by the company's beta.

After measuring the first dimension, it is necessary to look at the second dimension, namely, the management. First, it is necessary to measure the manageable risk which equates to the manageable risk factor (MRF) multiplied by the company's exposure (**cf. supra p.23**). Then, Sustainalytics determines how much of the manageable risk is effectively addressed (managed risk). It is an appraisal of a company's skill and effectiveness in managing its ESG and corporate governance issues. Management scores are marked from 0 to 100, where 0 indicates no management of the issue and 100 represents very strong management of the issue. For each material ESG issue they identified at the sub-sector level, they then selected and weighted the management metrics so that they would collectively deliver the best possible feedback to explain and measure how an average company in a sub-sector is managing the issue. The score for the managerial dimension is based on two underlying indicators. On the one hand, there is the“management preparedness” which refers to management's readiness and capacity to face ESG risks. On the other hand, there is the capacity of management to implement its measures in the system. This is measured through quantitative data or events such as controversies that have occurred in past situations.

Finally, the last step of computing Sustainalytics’ ESG risk rating is to define the unmanaged risk which is equal to the difference between the exposure and the managed risk. Consequently, this is broken down into two components: “the unmanageable risk, which cannot be possibly addressed by company initiatives, and the management gap, which represents risks that could be managed by a company through suitable initiatives, but are not yet being managed” (Sustainalytics, 2018, p.34) (**APPENDIX XIII: Risk decomposition and calculation of the unmanaged risk score & APPENDIX XIV: Building blocks of ESG risk ratings**).

Figure 2.2: Risk decomposition

Source: Garz, H., Volk, C., & Morrow, D. (2018). The ESG Risk Ratings. Moving Up the Innovation Curve, White Paper, 1.

To conclude, Sustainalytics (2018) is a tool that allows investors to compare companies with each other through their ESG scores and therefore allows a cross-sectoral approach with the possibility to compare companies in the same sector with a best-in-class approach. We can thus say that ESG ratings that are provided by Sustainalytics are absolute measures of risks. In other words, the scores and ratings can be compared to one another.

3 Chapter: Modern Portfolio Theory and Socially Responsible Investment

In general, the problem of portfolio optimization is solved by using the following parameters: the expected return (μ) and the standard deviation (σ) (**cf. supra p.7**). Nevertheless, we can observe that many academics have considered incorporating other parameters into the model developed by Harry Markowitz to achieve a more realistic and complete portfolio optimization and so answering investors' needs. Metaxiotis (2019) explains in his article *A Mean-Variance-Skewness Portfolio Optimization Model* that the desire for incorporating new parameters into classical portfolio optimization models is not recent. Indeed, portfolio optimization is a central theme in finance, and this is the reason why many researchers try to contribute to it.

In this chapter, we will study the existing literature on this subject to draw inspiration for the empirical part. We will take a closer look at the authors' reasons for writing their articles, their methodology, their conclusions, and finally, their suggestions for improving the research theme.

3.1 A three-dimensional approach to the Mean-Variance model

As a starting point, we observe in the literature that the incorporation of an additional variable in Harry Markowitz's model has already been done before.

In his paper, Metaxiotis (2019) incorporated skewness into Modern Portfolio Theory model with new algorithms. In Modern Portfolio Theory, asset returns are considered to follow the Gaussian distribution (**APPENDIX VII: Limits of Modern Portfolio Theory**). This is the reason why assets can be described by the central first and second moments of distributions. Nevertheless, it has been repeatedly demonstrated that asset returns do not have a normal distribution (Jondeau, Poon, and Rockinger, 2007). This can be characterized by skewness which represents the asymmetry level observed in a probability distribution (Lassance, 2021). In his work, the author's objective was to maximize return and skewness and minimize risk (Formulas **3.1**, **3.2**, **3.3**, and **3.4**). The

Mean-Variance-Skewness (MVS) portfolio optimization model considers thus these three parameters simultaneously with the following relationships:

$$f(w) \ = \ (f_1(w), f_2(w), f_3(w)) \tag{3.1}$$

$$f_1(w) = \sum\nolimits_{i=1}^{N} w_i \bar{r}_i \tag{3.2}$$

$$f_2(w) \ = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{3.3}$$

$$f_3(w) \ = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} w_i w_j w_k S_{ijk} \tag{3.4}$$

$Where$
$w\ and\ \bar{r}_i\ are\ the\ weight\ in\ the\ portfolio\ and\ the\ return\ of\ security\ i$
$\sigma_i is\ the\ standard\ deviation\ of\ security\ returns\ i$
$\rho_{ij}\ is\ the\ correlation\ between\ security\ i\ and\ j$
$S_{ijk}\ is\ the\ coskewness\ between\ securities\ i, j, and\ k$

For solving this optimization problem, Metaxiotis (2019) chose to apply an adapted and improved version of NSGAII. This software develops elaborated algorithms, incorporates constraints, and obtains results for problems considered unsolvable. He then used the FTSE-100 database to validate the model. Metaxiois (2019) contributed to the literature by proposing an extension of the Mean-Variance (MV) model. Moreover, he enriched existing literature by using a multi-objective evolutionary algorithm (MOEA) to deal with the difficulty of introducing a third central moment in the model.

Following the same principle, Jacobs and Levy (2013) decided to incorporate an additional parameter in what they call the GPSM (General Mean-Variance Portfolio Selection Model). Briefly summarized, the GPSM refers to Modern Portfolio Theory and its model. The authors consider that the GPSM does not take into account risk components that are unique to using leverage. According to them, "these include the risks and costs of margin calls - which can force borrowers to liquidate securities at adverse prices due to illiquidity - losses exceeding the capital invested, and the possibility of bankruptcy" (Jacobs and Levy, 2013, p.1). To develop their Mean-Variance-Leverage (MVL) model, they also considered investors' leverage aversion and incorporated it into the utility function, which usually only considers the expected return and the risk aversion of investors. This new model provided new efficient frontiers that have been compared to those provided by the MV model. The authors concluded that the MVL model allowed investors to consider their tolerance to volatility but also their leverage tolerance and were able to address one of the shortcomings of the MV model. Indeed, using leverage constraints with a standard GPSM, as it is mostly done today, is likely difficult to arrive at the portfolio that offers the most utility to a lever-averse investor. Yet, thanks to the new MVL model, investors can find optimal portfolios that simultaneously reconcile expected return, volatility risk, and leverage risk (Jacobs and Levy, 2013).

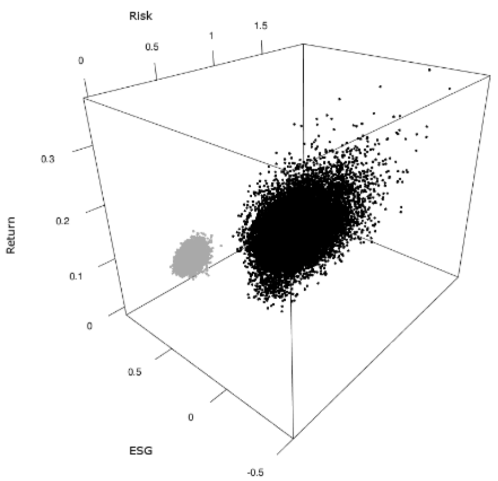
3.2 Social responsibility and portfolio optimization

As explained in previous sections of this thesis, the notion of sustainability is increasingly prominent in finance and the portfolio optimization process. We noticed in the literature that several academics have tried to solve this gap by integrating this aspect into Modern Portfolio Theory. However, they have chosen different methodologies, empirical approaches, variables, and samples. This is precisely why we first examined and reviewed these articles to gather inspiration from them for the second part of this thesis.

Gasser *et al.,* (2017) conducted a research paper for *The European Journal of Operational Research* in which they incorporated an additional criterion to Markowitz's model. They decided to add social responsibility to the two first parameters used. The objective was to build a multi-criteria decision model for investors who pay attention to social impact when making investment decisions. For doing so, they established a few preference parameters for return (μ), risk (σ), and social responsibility (θ). Taking these preferences into account, they created an *a priori* model to find the optimal portfolio for a specific investor. It is also possible to use the model without considering the preference parameters. This results in an *a posteriori* model that illustrates all optimal portfolios on the Capital Allocation Plane (CAP). The CAP can be compared to the Capital Allocation Line (CAL) as it enables investors to choose a portfolio that suits their preferences while considering all three optimization parameters and selecting their asset allocations.

Finally, Gasser *et al.*, (2017) conducted an empirical analysis and applied their *a posteriori* model to a sample of 6,231 international listed stocks by incorporating the ESG score collected from the ASSET4 ESG database. They analyzed relationships between the market situation and the studied parameters. The first observation is that investors with a strong preference for socially responsible investments had a lower return expectation than others. Opting for a socially responsible portfolio implied the acceptance of a significant drop in return. Risk also decreased. But important is to mention that the Sharpe ratio (θ/σ) is lower than the one of a classical optimized portfolio (μ/σ). Nevertheless, Gasser *et al.*, (2017) explained that it was feasible to invest in a portfolio with moderate social responsibility while accepting a slight reduction in the Sharpe ratio. This required applying an exclusion strategy (excluding assets that did not have a positive social impact) and then optimizing these assets according to μ/σ.

Figure 3.1: 3D View of the Capital Allocation Plane (CAP); return, risk, and ESG



Source: Gasser, S. M., Rammerstorfer, M., & Weinmayer, K. (2017). Markowitz revisited: Social portfolio engineering. *European Journal of Operational Research*, *258*(3), 1181-1190

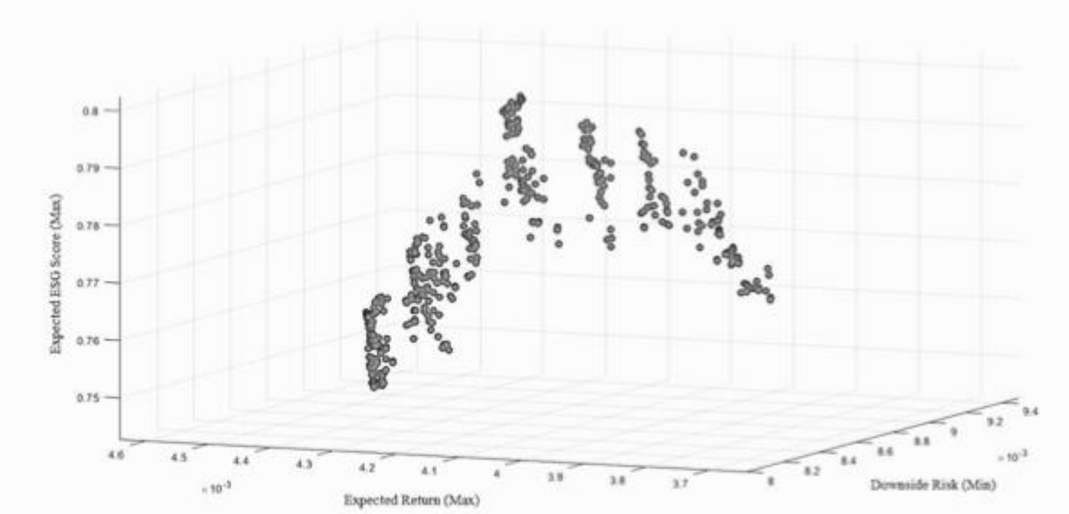
Continuing with the same approach, Garcìa, Gonzàlez-Bueno, Olivier, and Riley (2019) have noted that the portfolio selection problem was usually solved by an application of quantitative methods. Therefore, they contributed to the literature by introducing a fuzzy multi-objective approach. Its purpose was to "optimize the expected return, the expected ESG score, and the downside risk of a given portfolio, subject to real-world constraints such as budget, floor-ceiling and cardinality" (Garcìa *et al.*, 2019, p. 10). To capture the portfolio's performance and ESG score, Garcìa *et al.*, (2019) used the credibility mean, and to quantify the portfolio's downside risk, they used the credibility mean-absolute semi-deviation (MASD). The authors believed that downside risk was a more appropriate measure than variance as it takes into account the fact that investors are more sensitive to losses than gains. They conducted an empirical analysis using a data set from Bloomberg's ESG data in combination with Dow Jones Industrial Average (DJIA).

They applied their model and analyzed it to a sample of 29 companies between February 2014 and December 2017. Finally, they used a multi-objective approach for developing their model which optimizes expected return, minimizes risk, and maximizes ESG. For solving this optimization problem, they applied the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The efficient portfolio on the frontier was then identified from the Sortino ratio rather than the Sharpe ratio as it uses "downside measures rather than dispersion measure as the measure of risk" (Garcìa *et al.*, 2019, p.3). Consequently, it was more suitable for the chosen parameters.

They then compared the portfolio with the highest Sortino ratio with its benchmark (SPDR Dow Jones ETF (DIA)). They found that the socially responsible portfolio offered a slightly higher return and ESG score for an increased Value at Risk (VaR). The authors concluded this observation by stating that this research provided "promising results for SR-investors seeking ethical and sustainability goals beyond the return - risk trade-off" (Garcìa *et al.*, 2019, p.9).

Through this study, they were able to draw several conclusions. First, they demonstrated that the use of Bloomberg on the US Dow Jones was relevant for obtaining an ESG score. Second, they created a model that allows investors to find a socially responsible portfolio by considering the uncertainty of these securities and correctly assessing their risk. Finally, they validated the use of the Sortino ratio to determine the optimal portfolio on the efficient frontier. Nevertheless, the authors of this paper have highlighted the limits of their study. As an example, they suggested that research should be conducted with other ESG scores or using a different risk measure such as the Value at Risk (VaR).

Figure 3.2: Approximated Pareto-front generated by Non-dominated Sorting Genetic Algorithm II(NSGA-II) for the MDRSR model



Source: García, González-Bueno, Oliver, & Riley. (2019). Selecting Socially Responsible Portfolios: A Fuzzy Multicriteria Approach. Sustainability, 11(9), 2496.doi:10.3390/su11092496

Pederson *et al.,* (2020) also believed that a major shortcoming of Modern Portfolio Theory is the fact that the portfolio optimization process does not include the ability to incorporate ESG criteria in addition to risk and return. Consequently, they proposed a new model relying on the ESG-adjusted Capital Asset Pricing Model. This model included the ESG data of the portfolio's securities and created an ESG-efficient frontier.

As aforementioned (**cf. supra p.15**) there is a debate about the financial performance of ESG securities. This is also one of the questions raised by Blackrock in 2020 (Financial Times, 2020): "How do you incorporate ESG into your investment views, and does it really raise your returns or does it lower your returns?" (ESCP Finance Society, 2020, p.1). Pedersen *et al.*, (2020) used taste-based discrimination and statistical discrimination theories in their paper to answer that question. These theories explain that ESG scores might be associated with higher returns while other measures might imply lower returns. Firstly, as mentioned earlier, it seems as though ESG securities provide information about the future risks of the company (ESCP Finance Society, 2020). Secondly, taste-based discrimination theory states that ESG stocks would be preferred over non-ESG stocks. In addition, Pedersen *et al.*, (2020) referred to statistical discrimination according to which "different social groups have different properties, so, even if you're not having a taste against low ESG-stocks you will update your beliefs on stock preferences" (ESCP Finance Society, 2020, para.4). These theories led the authors to separate investors into three distinct categories. The sorting derives from the classification of investors according to their risk aversion (Risk-lover, Risk-neutral, Risk-averse). Pedersen *et al.*, (2020) ranked investors according to their ESG sensitivity. Firstly, there are the U-type investors. This means that they are ESG unaware and focus on the risk-return tradeoff over ESG. Then there are the Type A or ESG-aware investors. These investors use ESG scores to update their beliefs about stocks even though they prefer the risk-return tradeoff. Finally, there are the motivated or M-type investors. They have a real interest in ESG and incorporate these data and scores into their decisions. In other words, they seek the optimal balance between maximizing return, minimizing risk, and maximizing the ESG score of the securities. Later in their paper, this classification will be useful for incorporating investors' ESG sensitivity into the utility function and identifying the optimal portfolio on the curve.

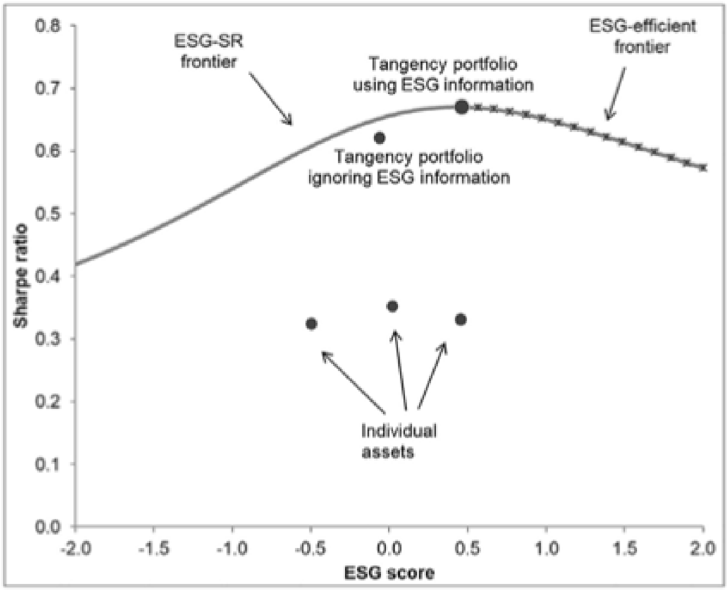
In the standard approach, investors only care about risk and return and opt for a combination of the tangent portfolio (the one with the maximum Sharpe ratio combined with the risk-free asset). However, Pedersen *et al*., (2020) suggested including ESG in the decision parameters. As a three-variable optimization problem is very complex, the authors preferred to use the Sharpe ratio (already incorporating risk and return) as well as the ESG score. This way, they were able to keep a two-variable optimization problem. Their objective was therefore to maximize the Sharpe ratio for a given ESG score.

To implement their model, Pederson *et al.*, (2019) used a portfolio of securities composed of risky and non-risky assets. Then, they calculated the ESG score based on each component. For E, they used the carbon emissions released by companies into the atmosphere. For S, they used the sin stock indicator. For G, they looked more closely at the aggressiveness of companies' financial statements. Finally, to get an overall idea of the aggregated ESG score, they used the score as defined on MSCI. They then applied their optimization objectives, namely maximizing the Sharpe ratio for a given ESG score level. This sequence of pairs allowed them to plot the efficient frontier which has a particular shape. It is in the form of a bell curve. The tangent portfolio represents the peak of the hump-shaped efficient frontier (Figure **3.3**). “To understand why the ESG-SR frontier is hump-shaped, consider first the tangency portfolio known from the standard mean-variance frontier, […]. This tangency portfolio has the highest SR among all portfolios, so its ESG score and SR define the peak in the ESG-SR frontier” (Pedersen *et al.*, 2020, p.2).

Using the new efficient frontier, which is also relying on the assumptions mentioned earlier (**cf. supra p.31**), Pedersen *et al.,* (2020) identify the portfolios that are selected according to the investor categories. First, A-type investors will opt for the tangent portfolio (the peak of the hump-shaped efficient frontier). As explained by the ESCP Finance Society (2020), ESG-aware investors will use ESG information without having a strong ESG preference and will maximize returns. Unaware investors will opt for a portfolio that will not optimize the Sharpe ratio as they will use suboptimal risk and expected return measures (ESCP Finance Society, 2020). Finally, M-type investors will be on the right side of the curve (where the ESG score is higher) and will not only consider the risk-return tradeoff but also the ESG components. One of the most impressive outcomes is the fact that Pedersen *et al.*, (2020) were able to quantify the cost and benefit of ESG information. A U-type investor would achieve a Sharpe ratio 12% lower than the maximum Sharpe ratio while an M-type investor would achieve only 4%. The benefit of ESG disclosure would therefore be much lower than the cost of ignoring ESG.

It should, however, be highlighted that this model is based on one major assumption which should not be overlooked. This assumption is the following: the ESG will have an important informational role in the future. Finally, the authors have contributed to the literature by proposing a model that enables investors to take into account their ESG preferences while having securities’ ESG information. Consequently, this is a different approach than the seven strategies of sustainable responsible finance such as, for example, negative screening (**APPENDIX VIII: Socially Responsible Investment strategies**).

Figure 3.3: ESG-efficient frontier



Source: Pedersen, L. H., Fitzgibbons, S., et Pomorski, L. (2020). Responsible investing: The ESG-efficient frontier. Journal of Financial Economics.

Similar to previous studies, Mercerau and Melin (2020) identified the pain point that is the lack of investment tools capable of taking into account the climate emergency. Therefore, they decided to develop an optimization tool that could take this new need into account.

First, they extended Harry Markowitz's model by adding the impact on the environment as a third dimension. This impact was measured using the carbon intensity of the companies under consideration. In the first model, the utility function was not modified, and they considered a rationnal investor who choose his portfolio based on return and risk. Nevertheless, they assumed in a second step that the investor wanted to take the climate impact into account and had a maximum temperature target for his portfolio. “The optimization finds the best risk/return tradeoff under a maximum temperature of the portfolio. Running optimizations under various temperature constraints allows exploring potential tradeoffs between portfolio risk, return, and temperature. An investor can then decide which tradeoff to choose” (Mercerau and Melin, 2020, p.3).

Second, they proposed a more sophisticated model that considered the fact that the investor not only cares about return and risk but also about the climate impact of his portfolio. They proposed a modification of the classic utility function by adding a coefficient considering the aversion to temperature increase generated by the activities of the companies in the portfolio. This coefficient, called TA (Temperature Aversion), is between 0 and 1. « For instance, a temperature-aversion of 1 would mean that the investor's wellbeing is unchanged if his or her portfolio's expected return drops by 1pp while at the same time its temperature alignment has improved by 1°C" (Mercerau and Melin, 2020, p.3). This new modification ensures that the optimizer will trade off the portfolio with the best risk and return while taking into account its climate impact aversion.

Modern Portfolio Theory has only addressed financial performance in the past. Its direct application is not suitable for Socially Responsible Investments (Vo, He, Liu, and Xu, 2019). The authors listed hereinabove were eager to develop a classic and widely accepted model in finance to serve Socially Responsible Investment. These studies show that academics are exploring the possibility of working with the Markowitz model and selecting stocks based on different parameters than those usually observed today. It can also be added that authors seem to agree that favoring ESG in optimization comes at a cost in terms of financial returns.

3.3 Modified Sharpe ratio

As with Harry Markowitz's optimization model (**cf. infra p.25**), some academics such as Gregoriou and Gueyie (2003) have questioned the adequacy of the Sharpe ratio. Indeed, they explain that this performance measure has certain limitations when used to compare hedge funds for example. They believed that this risk-adjusted measure was not ideal when used to investigate investments with fat tails or non-normal returns. Therefore, they changed the denominator and used the Value at Risk (VaR). Vinod and Morey (1999) also came up with a new Sharpe ratio called "Double Sharpe ratio" to address the fact that the denominator is a random variable (which can make it difficult to sample the distribution) and that it only takes into accont the portfolio risk. They then applied a bootstrap methodology and incorporated the risk estimate to remediate the issue.

Although this has not been done extensively, the Sharpe ratio has been modified in the past. We observe that these modifications occurred on the denominator (on the risk measure).

Conclusion of the literature review

In this literature review, we have addressed three main chapters.

First, we reviewed Modern Portfolio Theory developed by Harry Markowitz in the 1950s. We then discussed the main concepts related to Modern Portfolio Theory. We noted that in the context of portfolio optimization in portfolio management, this model is of great use to managers. It allows allocating assets to find optimal tradeoffs and identify inefficient portfolios.

Second, we addressed the main new trend in finance which is Socially Responsible Investment (SRI). On the one hand, there is a particular interest in ESG on the part of investors. Indeed, some studies show for example that once a fund has been certified as ESG, capital flows tend to be directed towards these funds (Becker *et al.*, 2022). As a result, it can be concluded that there is a real willingness on the part of investors to invest in a different, more ethical, and more sustainable way. It is also apparent that regulation is drastically changing. The European Commission has played a major role in implementing new regulations for financial institutions and firms. Amongst these new regulations, we recall that non-financial reports will now have to be complete (NFRD and CSRD), financial institutions will have to be more transparent about their investment policy and products (SFDR), and investors' ESG sensitivity will be considered in discretionary management and advisory mandates (MiFID).

Finally, we observed that although Socially Responsible Investment (SRI) is booming, the portfolio optimization tool has not evolved since the 1950s. Modern Portfolio Theory is not yet able to respond to these needs and changes. We have therefore looked in chapter three at existing scientific papers that have attempted to revisit Modern Portfolio Theory to incorporate new parameters that can better meet investors' needs. We have mainly looked at the needs identified, the methodologies used, and the conclusions reached. There are a few models that have considered ESG in portfolio optimization and the one that has caught our attention the most is that of Pedersen *et al.*, (2020).

PART 2 – EMPIRICAL WORK

Introduction of the empirical work

In this second part of our thesis, we will get into the empirical part. This section is subdivided into three main chapters.

Firstly, we will discuss various elements of the chosen methodology. We will detail the research question and the hypotheses. Furthermore, we will describe the structure of the research, data collection tools, and data themselves.

Secondly, we will elaborate on three optimization models. We will give further explanations of the calculations and results. We will take a closer look at the efficient frontiers obtained and the tangent portfolio.

Thirdly, we will then compare those models and identify the differences between them. We will examine three main elements: efficient frontiers, tangent portfolios, and risk-return combinations. We will also investigate the estimated ESG scores for the different portfolios. In this way, we will be able to conclude on our optimization models that incorporate ESG criteria and compare them based on their performance.

Finally, we will discuss the limits of our research and we will conclude with the areas that could be further elaborated to refine the research and propose more accurate results.

4 Chapter: Methodology

The typology of this thesis is an applied research thesis. The contribution of the research paper is to address a concept that we have identified as problematic in the literature and to offer a solution. This typology choice has strongly influenced the methodology adopted for this thesis.

In this chapter, we will discuss the theme of the thesis and the hypotheses from which we started to answer the research question. We will then describe the methodology and data collection tools that we were able to define through our hypotheses, concepts, and dimensions.

4.1 Theme

4.1.1 Research question

As a reminder, the theme of this thesis is "the integration of the ESG criteria into the Modern Portfolio Theory: an analysis based on the BEL20". The research objective is to propose a straightforward portfolio optimization tool able to consider ESG scores in addition to return and risk. The purpose is therefore to answer the following question: **how to integrate ESG criteria into the Modern Portfolio Theory and how the efficient frontier and tangent portfolio will be impacted?** Consequently, this thesis will mainly focus on Modern Portfolio Theory initially developed by Harry Markowitz and on Socially Responsible Investment.

In the first stage, we will construct an optimized portfolio of 20 stocks replicating the BEL20 index using Modern Portfolio Theory. In this way, we will be able to plot the efficient frontier and to identify the tangent portfolio. In a second phase, we will optimize the same portfolio with the help of revised models of Modern Portfolio Theory, this time integrating ESG criteria by using the Sharpe ratio and a reviewed Sharpe ratio.

4.1.2 Hypotheses

In answering this question, we decided to define two assumptions that will be used as a starting point for our reasoning throughout this thesis. These hypotheses will then be refuted or confirmed.

<u>Hypothesis 1 (SR - ESG risk rating):</u> **if** we integrate ESG risk rating within the optimization model, **then** the efficient frontier will shift to the right, adopt a concave shape, and the tangent portfolio will remain the same.

<u>Hypothesis 2 (ESG SR - SD)</u>: **if** we integrate ESG risk ratings within the optimization model, **then** the efficient frontier will adopt a concave shape, become flatter, and the tangent portfolio will deteriorate as we added a new constraint.

Useful dimensions and concepts for answering those hypotheses have been defined in the literature review (efficient frontier, tangent portfolio, risk, return, Sharpe ratio, and ESG risk rating).

As this theme has already been the subject of various research studies in the past, these hypotheses relate to an area that has been previously observed and will therefore be used rather as a testing of the impact of the integration of ESG criteria in Harry Markowitz's model on the efficient frontier. As a result, we can also conclude that we are treating this as an explanatory and not as a descriptive hypothesis (Paquet, Bawin, Schrooten, and Wattier, 2016).

4.2 Choice of the methodology

For conducting this thesis, we have chosen to use a quantitative methodology. The latter is more appropriate in the financial context of this thesis. Quantitative methodologies are research methods, using mathematical and statistical analysis instruments, to describe, understand and predict events using historical data in the form of measurable variables (Schütte, 2002).

4.3 Description of the proposed research structure

4.3.1 Data collection tools and pretesting of data collection tools

The quantitative methodology chosen to address the research question and to test hypotheses leans toward the use of quantitative data collection tools. Nevertheless, for completing results obtained and to confront them with the professional world, quantitative data will be supplemented by qualitative data.

This thesis is predominantly constructed from secondary data but will be supplemented by primary data.

First, we used two types of data collection tools which are secondary data. On the one hand, we used scientific documents written by academics and which have been submitted to the proofreading and validation process. On the other hand, we used data from professional sources such as reports from consulting firms. These enabled us to support some facts and trends observed in the financial industry and to develop a few concepts. They also provided us with the opportunity to support what academics developed in their research papers with information from the field.

Second, we used statistical and numerical data also considered as secondary data. These data were used in the empirical part. Indeed, to optimize the BEL20 portfolio, we had to retrieve historical prices from Bloomberg. In addition, we retrieved the ESG risk ratings of the 20 companies from Sustainalytics (**cf. supra p.23**). Such data have been carefully collected over a valid period and will be useful for testing the hypotheses (Paquet, Schrooten, and Simons, 2020).

Finally, as mentioned hereinabove, we decided complete the results and the research elements collected with the reality of the field. Therefore, we also conducted interviews (primary data) with people working at Degroof Petercam (internship location). These interviews were semi-directed (**APPENDIX XXV & XXVI: Semi-directed interview guides**).

4.3.2 Composition and size of the sample

The sample we decided to work on is the BEL20 over a period of 3 years. “The BEL 20 is a Belgian index providing information on the general share price of twenty companies. It consists of shares issued by companies selected by Euronext, an international stock exchange company, based on strict criteria: they must have a significant free-floating market capitalization, display a minimum velocity (35% of the shares issued by the company must have changed hands) and hold sufficient liquidity. Companies listed on the BEL20 do not have to be Belgian, but must be active in Belgium” (BeoBank, 2022, para.1).

Historical price data for the BEL20 index over a monthly period (from 04/29/2019 to and including 04/29/2022) were retrieved from Bloomberg. Data for the risk-free rate (represented by the Belgian 10-year risk-free rate) was collected from Bloomberg on 29 April 2022, the day we gathered all the statistical and numerical data.

Regarding the ESG risk ratings, we collected data from the provider Sustainalytics on 29 April 2022. Nevertheless, it is important to mention that there is no historical score on Sustainalytics. Scores are reviewed when an event has an impact on one of the dimensions considered for the score. As a result, scores that have been retrieved are representative of a given time. We will come back to this aspect later in the limits of our analysis (**cf. infra p.62**).

4.3.3 Data analysis method

For the construction of the methodology, the analysis, and the processing of data, we drew on elements collected in the literature review. Indeed, we identified some articles and authors who already integrated ESG criteria in Harry Markowitz’s model and proposed an alternative to the classical optimization problem.

The method of analysis we chose is comparative. Indeed, as briefly explained above (**cf. supra p.39**), we decided to answer the research question by first studying the efficient frontier obtained by optimizing the portfolio representing the BEL20 using Modern

Portfolio Theory. Then, in a second step, we revisited Harry Markowitz's model by integrating Sustainalytics ESG risk ratings and by using the Sharpe ratio. In this way, we obtained a different efficient frontier, and tradeoffs. We then took this optimization one step further by suggesting a reviewed Sharpe ratio. Finally, we decided to compare these models to understand the impact of integrating ESG criteria. The comparative method idea came to us after reading the research conducted by Gasser *et al.*, (2017). They developed a first *a priori* model and a second *a posteriori* model. These two models were then compared to draw conclusions.

Next, the choice of our data sample was also inspired by the literature. We noticed that many academics had used databases from well-known rating agencies such as ASSET4 ESG, Bloomberg ESG, MSCI, or Sustainalytics. Some combined these scores with further individual analyses to get a more accurate score, while others simply used the scores as they were originally published (Garcià *et al.,* 2019; Vo *et al.,* 2019). As for the sample to be analyzed, we chose an index already existing. For example, in some papers, it was the Standard & Poor's 500 (S&P500) or the US Dow Jones Industrial Average (DJIA) (Vo *et al.,* 2019; Garcià *et al.,* 2019).

Subsequently, we took a closer look at the methodologies used by authors and the "core" of the empirical research. We decided to keep a two-dimensional optimization rather than adding one for reasons of research limitations. In addition, we also selected some elements to be analyzed in further detail. Risk and return are obviously among them. The Sharpe ratio also came up repeatedly in the articles reviewed (Gasser *et al.,* 2017; Pedersen *et al.,* 2020). "While optimizing across three characteristics (risk, return, ESG) can seem challenging, we show that the investor's problem can be reduced to a trade-off between ESG and Sharpe ratio. In other words, risk and return can be summarized by the Sharpe ratio" (Pedersen *et al.,* 2020, p.2).

Finally, regarding the conclusions, we will not only compare the three models, but we will also refute, confirm, or complete conclusions previously drawn by the authors. In addition, we will discuss the relationship between portfolio performance, risk, return, and ESG. This is a topic that generates a lot of debates and has been mentioned many times in scientific articles.

The following analysis will therefore be divided into three main parts. The first focus solely on the Mean-Variance (MV) portfolio optimization of the BEL20 portfolio. The second builds on the work of academics previously carried out, and on the article by Pedersen *et al.,* (2020) to integrate ESG criteria into Modern Portfolio Theory optimization model (Sharpe Ratio - ESG risk rating). Finally, the last one will focus on optimization using the ESG Sharpe ratio and risk (ESG Sharpe ratio - Standard deviation).

The different steps for the optimization and the calculations will be detailed in chapter 5 (**cf. infra p.44**).

5 Chapter: Empirical analysis, results, and models' comparison

We will examine in this chapter findings of our three models. We will then compare these models and their results. Finally, we will discuss the limits of this analysis.

5.1 Preliminary calculations

After having collected relevant data, we will proceed to the calculation of a return and the risk of the stocks composing the portfolio.

For this purpose, we calculated the historical mean returns of each of the stocks for the past 3 years using the appropriate formula which is the continuously compounding return formula as returns are additive over time (Lassance, 2021).

$$R_i = ln\, \frac{P_i - P_{i-1}}{P_{i-1}} \tag{5.1}$$

We then computed an average of these monthly returns. We used the arithmetic mean formula to do so (D'Hondt, 2021) (**APPENDIX XXVII: Risk-return calculations**).

$$\overline{R}_i = \frac{R_{i1} + R_{i2} + \ldots + R_{iT-1} + R_{iT}}{T} = \frac{1}{T}\sum_{i-1}^{T} R_{iT} \tag{5.2}$$

We also determined the variance and the standard deviation of these monthly returns for each stock. Since it is based on the monthly returns, the variance is also calculated monthly (**APPENDIX XXIV: Return / standard deviation / variance**).

Then, based on monthly returns, we were able to calculate the variance-covariance matrix. Since the portfolio represents the BEL20 index with 20 stocks, we obtained a matrix with 20 rows and 20 columns (**APPENDIX XXV: Covariance matrix**).

For optimizing the selected portfolio of securities, we also required a risk-free rate. The risk-free rate we have used is the 10-year Belgian Treasury rate. We used the rate as of 04/29/2022 which was equivalent to 1.45% and the monthly rate is 0.12%.

$$Rf_{monthly} = Rf_{annual}^{(1/12)} \tag{5.3}$$

Finally, we calculated the correlation between each of the stocks in the portfolio to see how they work together (**APPENDIX XXVI: Correlation matrix**).

5.2 Mean-Variance portfolio optimization

As explained earlier in chapter 5 (**cf. supra p.40**), we started with the assumption that the portfolio was equally weighted. Consequently, we hypothesized that 5% (100% / 20) of the portfolio was invested in each of the securities.

$$w_i^e = \frac{1}{N} \tag{5.4}$$

$Where$
$w \text{ is the weight allocated to each security}$
$N \text{ is the number of securities}$

With this assumption, we were able to calculate the portfolio return, variance, standard deviation, and Sharpe ratio.

We used the Solver as an optimization tool and set different constraints. First, the sum of the weights should be equal to 1.0. Second, the use of leverage was not authorized (**APPENDIX XVIII: Mean-Variance optimization methodology**).

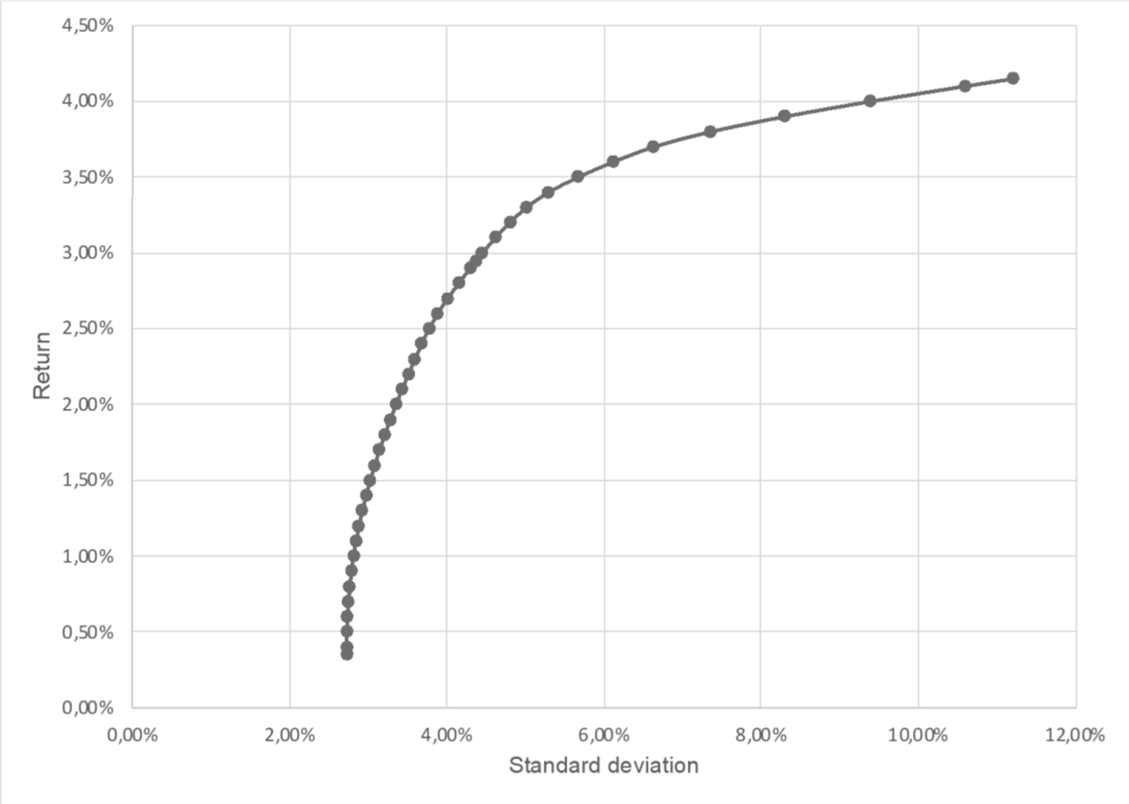
$$\sum_{i=1}^{N} w_i = 1 \tag{5.5}$$

$$w_i \geq 0 \tag{5.6}$$

Once the constraints set, we used the Solver to optimize the portfolio. For doing so, we sought to minimize the portfolio's variance while adjusting the weights invested. The result obtained by the Solver considering these constraints was a portfolio with a standard deviation of 2.73%, a return of 0.35%, and a Sharpe ratio of 0.082. This represents the minimum variance portfolio.

After identifying the minimum variance portfolio, we applied a new constraint in the Solver. We specified a return level to be achieved while trying to minimize the variance. We then performed about 40 iterations to obtain risk-return combinations for the portfolio. From the various pairings, we were able to draw the efficient frontier in the risk-return space. Similarly, we were able to identify the tangent portfolio. We will further detail these results in the following section.

Figure 5.1: Mean-Variance efficient frontier



Source: Empirical analysis

5.2.1 Results of Mean-Variance portfolio optimization

If we look at the tangent portfolio as defined by Vo *et al*., (2019), we observe a standard deviation of 4.37% for a return of 2.94%. The Sharpe ratio is equivalent to 0.6469 (**APPENDIX XXXIII: Mean-Variance tangent portfolio**).

We also examined the case where the portfolio would achieve the minimum variance for the highest possible return. Thanks to the correlation between assets and the phenomenon of diversification, the minimum variance to be achieved is lower than the variance of Groupe Bruxelle Lambert (GBL), which is the lowest of the 20 stocks forming the BEL20. In this case, the variance would be equivalent to 0.07%, with a standard deviation of 2.73% and a return of 0.35% (**APPENDIX XXXII: Mean-Variance minimum portfolio**).

We obtain a classical shape for this efficient frontier. The further we move to the right, the higher the expected return. Yet, it is important to highlight that the risk will also increase. This is normal as there is no free lunch on the efficient frontier. Indeed, it is not possible to move along the efficient frontier to obtain a higher return without increasing risk. This is reflected in the slope becoming less and less steep. This means that the risk load to be borne will be higher for achieving a slightly higher return. Consequently, we can conclude that the Sharpe ratio deteriorates because the risk-return relationship becomes less attractive.

5.3 Sharpe ratio - ESG risk rating portfolio optimization

In this case, we proceeded differently as we had to incorporate the ESG risk rating in the model.

As in the first model, we proceeded with the same preliminary calculations (**cf. supra p.45**) and we assumed that the model was equally weighted (**cf. supra p.46**).

Then, we computed the average ESG risk rating of the portfolio. For doing this, we used data from Sustainalytics and applied the same formula when computing the portfolio return. This is the sum of the products. In practice, we multiply the ESG risk ratings of each stock by their weights and then calculate the weighted average of this result.

$$ESG\ risk\ rating_{\ P} = \sum_{i=1}^{N} w_i ESG\ risk\ rating_i \tag{5.7}$$

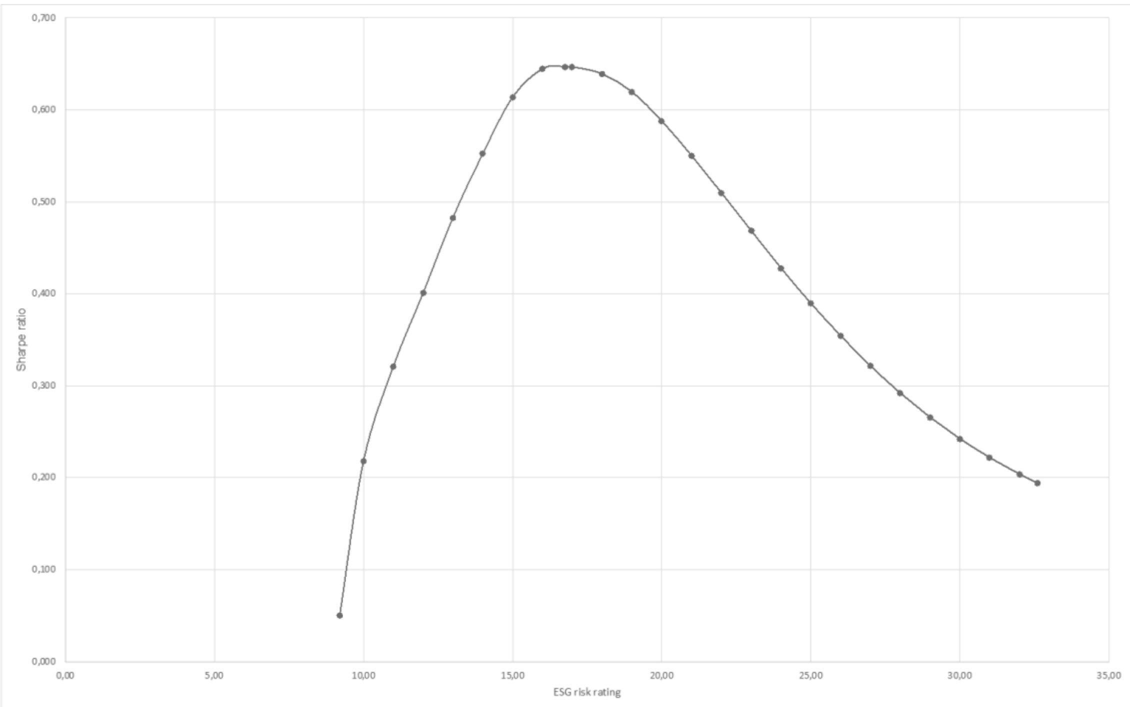
This step completed, we computed the portfolio return, the portfolio variance, the standard deviation, and the Sharpe ratio.

Regarding the optimization process, we have modified the method as described by Modern Portfolio Theory. Indeed, we maintained the initial constraints, which are that there is no use of leverage and that the total weight invested must be equal to 1.0 (**cf. supra p.46**). However, using the Solver, we chose to maximize the Sharpe ratio while adjusting the weight invested (**APPENDIX XIX: Sharpe-ratio ESG risk rating optimization methodology**).

Then, to obtain enough pairs to draw the efficient frontier, we added a new constraint. We attempted to maximize Sharpe Ratio for a defined ESG score. We performed about 40 iterations for having enough pairs to draw the efficient frontier. The ESG risk rating constraint ranged from 9.2 (100% of the weight invested in Groupe Bruxelles Lambert) and 32.6 (100% of the weight invested in Argenx). As a reminder, we saw in chapter 2 of the literature review (**cf. supra p.23**) that the score given by Sustainalytics represents an ESG risk rating. Consequently, the objective is to minimize this score. The lower the score, the better, as the company has fewer ESG risks.

With all these Sharpe ratios - ESG risk rating pairs, we were able to plot the efficient frontier. However, since we changed the parameters considered for the optimization, we also had to modify the x-axis and the y-axis. Indeed, with this new optimization model, the x-axis represents the ESG risk rating while the y-axis is the Sharpe ratio (**APPENDIX XXXIV: Sharpe ratio - ESG risk rating risk-return pairs**).

Figure 5.2: Sharpe ratio - ESG risk rating efficient frontier



Source: Empirical analysis

It should also be highlighted that the remaining part on the right of the frontier after the peak of the frontier can be considered inefficient since a better ESG score can be obtained for the same Sharpe ratio (Figure **5.2**).

5.3.1 Results of Sharpe ratio - ESG risk rating portfolio optimization

We observe that the tangent portfolio has a Sharpe ratio equivalent to 0.6469 for an ESG risk rating of 16.76. In that case, the portfolio expected return is equal to 2.94% with an associated standard deviation of 4.37%. The ESG risk rating is around the median of the scores (17.3). This result is therefore not excellent insofar as the Sharpe ratio is not greater than 1.0.

Regarding the efficient frontier, it has a hump shape, and it has shifted sharply to the right. This is understandable as the x-axis represents the ESG risk rating and the minimum achievable is 9.2 as discussed above.

It can also be observed from Figure **5.2** that an increase in the Sharpe ratio implies a deterioration in the ESG score. However, what is worth mentioning is that once the tangent portfolio is reached on the efficient frontier, it is no longer possible to improve the Sharpe ratio. Indeed, as the ESG score continues to deteriorate, we observe that the Sharpe ratio also becomes worse.

5.4 Comparison between Mean-Variance portfolio optimization and Sharpe ratio - ESG risk rating portfolio optimization

After having analyzed the results of both models, we will now compare our findings and discuss their implications.

5.4.1 Efficient frontiers

Firstly, efficient frontiers have not been constructed with the same method. In the first case, we applied Modern Portfolio Theory and identified the tangent portfolio by obtaining the highest return while minimizing the risk load. In the second case, we incorporated ESG risk ratings. To keep the optimization two-dimensional, we used the Sharpe ratio. The latter allowed us to consider risk and return while adding ESG risk rating as a second parameter in the optimization problem. As a result, we have obtained two very different efficient frontiers in terms of shapes and risk-return couples.

Nevertheless, both frontiers depend solely on the characteristics of the securities and are therefore independent of investors' preferences (Pedersen *et al.*, 2020).

In the Mean-Variance model, the function is increasing with a slope that flattens out as it progresses. This confirms what Modern Theory explains since if investors are interested in obtaining a higher return, it implies that they must move to the right on the efficient frontier and consequently accept an additional risk load. In the second case, the efficient frontier shifts slightly to the right and is hump-shaped. Similarly, to the Mean-Variance model, the slope is steeper at the beginning and flattens out as it goes along.

5.4.2 Tangent portfolios and Sharpe ratios

At the end of this first approach to incorporate the portfolio's ESG score in the optimization, we note that our results are quite similar to those obtained by Pedersen *et al.*, (2020).

The Sharpe ratio of the tangent portfolio obtained in the SR-ESG risk rating model is identical to the one obtained with the MV optimization method (0.6469). Our observations are in line with those of Pedersen *et al.*, (2020) as they explained that the peak of the hump-shaped efficient frontier was the Sharpe ratio, and it was the same as the one obtained with the standard tangency portfolio. Likewise, we also noticed that if investors wish to improve their portfolio in terms of ESG (move to the left), the portfolio’s Sharpe ratio will become lower. A better ESG score implies a deterioration of the Sharpe ratio. Conversely, if investors do not want to take ESG into account, they will opt for a portfolio on the right of the tangency portfolio and lose performance.

This result is not surprising given that in the first case, the tangent portfolio is the one with the highest Sharpe ratio. Similarly, in the second optimization, we tried to identify the portfolio with the highest Sharpe ratio while considering the ESG score of the portfolio.

If we now consider the utility function and the indifference curves (investors' risk and return preferences), we notice that investors with a low-risk tolerance will be on the left side of the efficient frontier in the MV model. To take this factor into account in the SR-

ESG risk rating model, it is necessary to modify the parameters used in the utility function. Pedersen *et al*, (2020) have already done this work in their research paper and classified investors into three broad categories according to their ESG sensitivity: (1) Type-A, (2) Type-M, and (3) Type-U (**cf. supra p.32**). If we use the same categorization, it can be concluded that investors with low ESG sensitivity (Type-A) are more likely to choose the tangent portfolio, which is the peak of the hump on the plot (Figure **5.2**). Investors with high ESG sensitivity who wish to hold a portfolio with low ESG risk (Type-M) will tend to be on the left side of the efficient frontier, even if it means choosing portfolios with lower Sharpe ratios than the optimal portfolio (Figure **5.2**). Finally, investors who are not sensitive to the ESG score (Type-U) could choose the tangent portfolio or portfolios on the right of the frontier (Figure **5.2**).

5.4.3 Risk-return combinations

Although tangent portfolios defined by the two optimization models are identical, the risk-return pairs generated are quite different. Indeed, if we place the SR-ESG risk rating's efficient portfolios in the universe of Modern Portfolio Theory (μ / σ), we notice that many pairs are below the frontier. This means that maximizing Sharpe ratios while imposing a constraint on ESG scores results in inefficient portfolios in Modern Portfolio Theory (it is possible to achieve a higher return for the same risk load or the same return for lower risk). One reason for this is that the classic efficient frontier offers efficient portfolios with an ESG score between 11.70 and 19.14 (its median equals to 17.70). Therefore, by using the SR-ESG risk rating model, we consider portfolios that do not fall within the scope of MV optimization.

As an illustration of this, if we look at portfolios of similar returns (Table **5.1**), we see that the MV portfolio for this return is the minimum variance portfolio. It is diversified and is made up of securities that are not highly correlated with each other (**APPENDIX XXXIII: Mean-Variance tangent portfolio**). If we turn to the SR-ESG risk rating portfolio for a return of 0.37%, we observe that it is entirely invested in Groupe Bruxelles Lambert (GBL) and has a higher risk load. As a result, this portfolio also has a lower Sharpe ratio and is not diversified, but it has a better ESG score.

<u>Table 5.1</u>: Comparison table Mean-Variance and Sharpe ratio - ESG risk rating

	Portfolio MV	Portfolio SR-ESG risk rating
Return	0.35%	0.37%
Risk	2.73%	5.07%
Sharpe ratio	0.085	0.050
ESG risk rating	19.63	9.20

Source: Empirical analysis

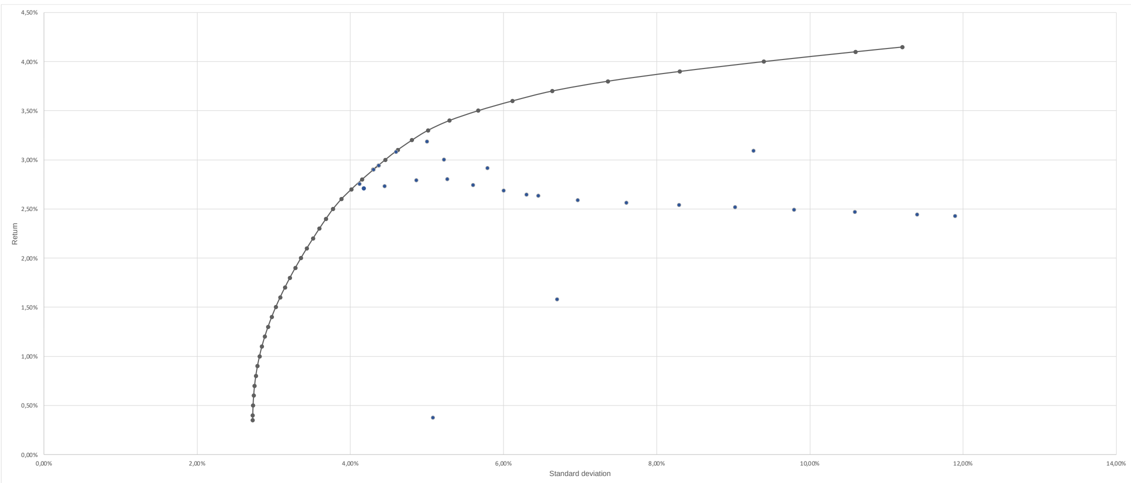
For a 3% return portfolio (Table **5.2**), an ESG constraint results in a modification to the portfolio composition towards securities with a better ESG score (i.e., GBL instead of Argenx and Ageas).

Table 5.2: Comparison table Mean-Variance and Sharpe ratio - ESG risk rating

	Portfolio MV	Portfolio SR - ESG risk rating
Return	3.00%	3.00%
Risk	4.45%	5.22%
Sharpe ratio	0.6468	0.5524
ESG risk rating	16.64	14.00

Source: Empirical analysis

Figure 5.3: Risk-return pairs of Mean-Variance and Sharpe ratio - ESG risk rating optimizations



Source: Empirical analysis

Figure's legend:

MV risk - return pairs

Imposing an ESG constraint for the best Sharpe ratio results in non-efficient SR-ESG risk rating risk-return couples according to Modern Portfolio Theory (except for a few portfolios). This is mainly because we impose ESG scores to be reached for which MV optimization does not provide efficient portfolios. Moreover, we could not have known this in advance, but MV efficient portfolios have generally relatively low ESG scores (**cf. supra p.50**). We can therefore argue whether it is worth opting for SR-ESG efficient portfolios given the slight difference in ESG scores. Perhaps the differences would have been greater if we had used a different sample.

The strength of this model is that it is easier for investors to visualize the ESG dimension of their investments. Using this revised model, the SR-ESG risk rating frontier is a convenient tool for illustrating the spectrum of investment opportunities when individuals care about risk, return, and ESG. It is possible to show what an improvement or deterioration in ESG score will cost in relation to the Sharpe ratio.

5.5 ESG Sharpe ratio - Standard deviation portfolio optimization

Using the SR-ESG risk rating optimization method, we noticed that tangent portfolios were identical and that optimizing based on the Sharpe ratio and the ESG score closely look like parameters used in an MV optimization. Therefore, we elaborated on this second optimization model to create a third one.

We started from the initial idea of using a ratio on the y-axis and the ESG score on the x-axis. Nevertheless, with the use of literature (**cf. supra p.33**), we imagined a new ratio whose logic was inspired by the Sharpe ratio. We choose the excess portfolio return as the numerator for this new ratio. As the denominator, we used the ESG score of the portfolio. The objective here is to maximize this ratio as we try to maximize the return while minimizing the Sustainalytics ESG score.

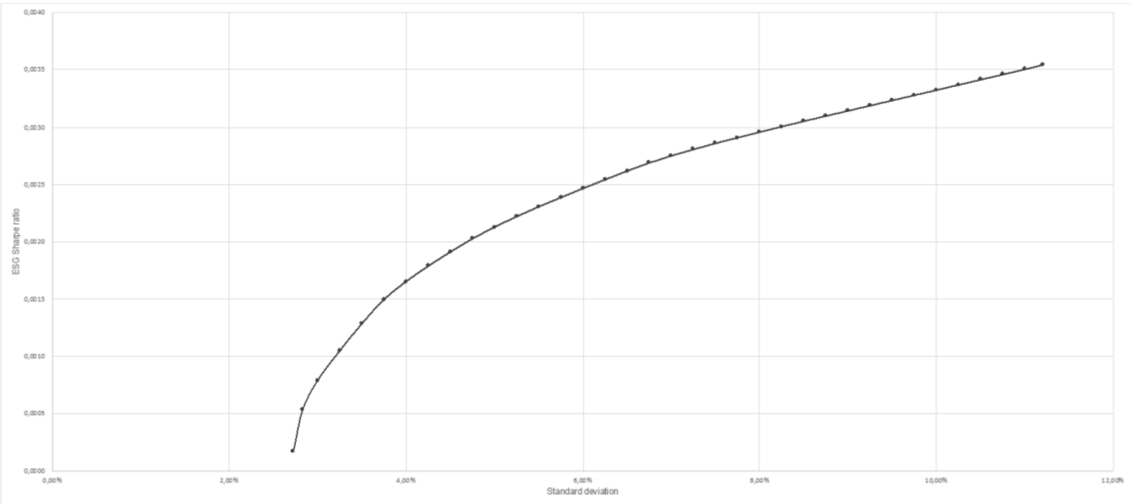
$$ESG\ Sharpe\ Ratio = \frac{R_p - R_f}{ESG\ risk\ rating} \tag{5.8}$$

After performing preliminary calculations (**cf. supra p.45**), we computed the portfolio return, the portfolio variance, the standard deviation, and the Sharpe ratio. The denominator (portfolio ESG risk rating) was computed using the same methodology as in the SR-ESG risk rating optimization model (**cf. supra p.48**).

This step completed, we thus applied the same constraints and assumptions as those previously used (equally weighted, no use of leverage, and the sum of the weights invested should be equal to one) (**APPENDIX XX: ESG Sharpe ratio - Standard deviation optimization methodology**).

We then proceeded with our optimization thanks to the Solver. The goal was to maximize the ESG Sharpe ratio for a given risk level. We performed a series of iterations to obtain enough pairs for drawing a new efficient frontier.

Figure 5.4: ESG Sharpe ratio - Standard deviation efficient frontier



Source: Empirical analysis

5.5.1 Results of ESG Sharpe ratio - Standard deviation portfolio optimization

The minimum variance portfolio has a standard deviation of 2.73% for an ESG Sharpe ratio of 0.000089. Its composition is identical to that of the minimum variance portfolio identified using Modern Portfolio Theory (**APPENDIX XXXIX: ESG Sharpe ratio – Standard deviation with highest ESG Sharpe ratio**). However, it is interesting to note that the Solver identified a portfolio 100% invested in D’ieteren as the portfolio with the highest possible ESG Sharpe ratio. Thus, we got a portfolio having a standard deviation of 11.21% for a return of 4.15% with an ESG Sharpe ratio equivalent to 0.0035 and a Sharpe ratio equivalent to 0.3596. This portfolio no longer benefited from the diversification effect.

5.6 Comparison between Mean-Variance portfolio optimization and ESG Sharpe ratio - Standard deviation

5.6.1 Efficient frontiers

Looking at the efficient frontiers, we can observe that the shape is close to the shape of the classical efficient frontier in contrast to results obtained with the SR-ESG risk rating optimization. This is mainly because we find the standard deviation on the x-axis. The frontier has neither shifted to the left nor to the right as both optimizations propose an identical portfolio for a minimum variance.

5.6.2 Tangent portfolios and Sharpe ratios

The portfolio with the highest Sharpe ratio is equivalent to 0.6333 with a return of 3.13% and a standard deviation of 4.75%. This portfolio has a more sustainable composition compared to the tangent MV portfolio. We, therefore, observe that the maximum obtainable Sharpe ratio is slightly lower than the one achievable with the Mean-Variance optimization (0.6469) (**APPENDIX XL: ESG Sharpe ratio - Standard deviation with highest Sharpe ratio**). This deterioration is observed as stocks with a higher ESG score (Argenx and Ageas) are removed from the portfolio and compensated by an additional weighting in other stocks. This, therefore, hurts the Sharpe ratio. All of this for a very slight difference between the ESG scores of the two portfolios (16.76 for the MV optimal portfolio against 15.42 for the ESG SR - SD optimal portfolio). In fact, when looking at the optimal portfolio composition according to Modern Portfolio Theory, the ESG score is already quite good.

Table 5.3: Comparison table Mean-Variance and ESG Sharpe ratio - Standard deviation

	Portfolio MV	Portfolio ESG SR - SD
Return	2.94%	3.13%

Risk	4.37%	4.75%
Sharpe ratio	0.6469	0.6333
ESG risk rating	16.76	15.42

Source: Empirical analysis

5.6.3 Risk - Return combinations

If we place the ESG Sharpe ratio risk-return pairs into the Modern Portfolio Theory framework using their return as well as their standard deviation, we notice that some risk - returns pairs are below the standard efficient frontier.

First, both optimization models indicate identical minimum variance portfolios. Then, we observe that by transposing the efficient portfolios identified by the third optimization method into the standard theoretical framework, risk-return couples corresponding to these portfolios are slightly below the MV efficient frontier, up to the portfolio with a standard deviation of 2.88% and a return of 1.2%. In this area, portfolios have a similar composition. Between these two points, the ESG SR - SD optimization proposes couples for which the return is identical but for an additional risk load.

The efficient portfolios of the two optimizations are then found on the same curve up to a standard deviation of 2.92% for a return of 1.3%.

From this point onwards, risk-return couples of the third optimization again form a curve below the standard efficient frontier. For example, we can observe that the MV and ESG SR - SD portfolios have an almost identical composition for a risk of 4.00% (Table **5.4**). In the first case, we can see that the portfolio is composed of Ageas (8.67%), Argenx (4.46%), D'ieteren (0.98%), Elia (37.54%), VGP (34.44%), and WDP (13.91%). The ESG Sharpe ratio - SD portfolio consists of D'ieteren (1.64%), Elia (30.63%), GBL (17.44%), VGP (32.44%) and WDP (17.82%). Weightings in stocks with poor ESG scores are reduced or eliminated.

Maximization based on the ESG Sharpe ratio resulted in a slightly lower return (with a deterioration of the Sharpe ratio) with an improvement of the ESG score for the same risk load.

Table 5.4: Comparison table Mean-Variance and ESG Sharpe ratio - Standard deviation

	Portfolio MV	Portfolio ESG SR - SD
Return	2.69%	2.46%
Risk	4.00%	4.00%
Sharpe ratio	0.6430	0.5846
ESG risk rating	17.29	14.86

Source: Empirical analysis

Finally, efficient portfolios are again on the same curve starting with the portfolio with a standard deviation of 6.25% and a return of 3.63%. The portfolios are identical with D'ieteren (33.04%), Elia (5.22%) and VGP (61.73%) (Table **5.5**).

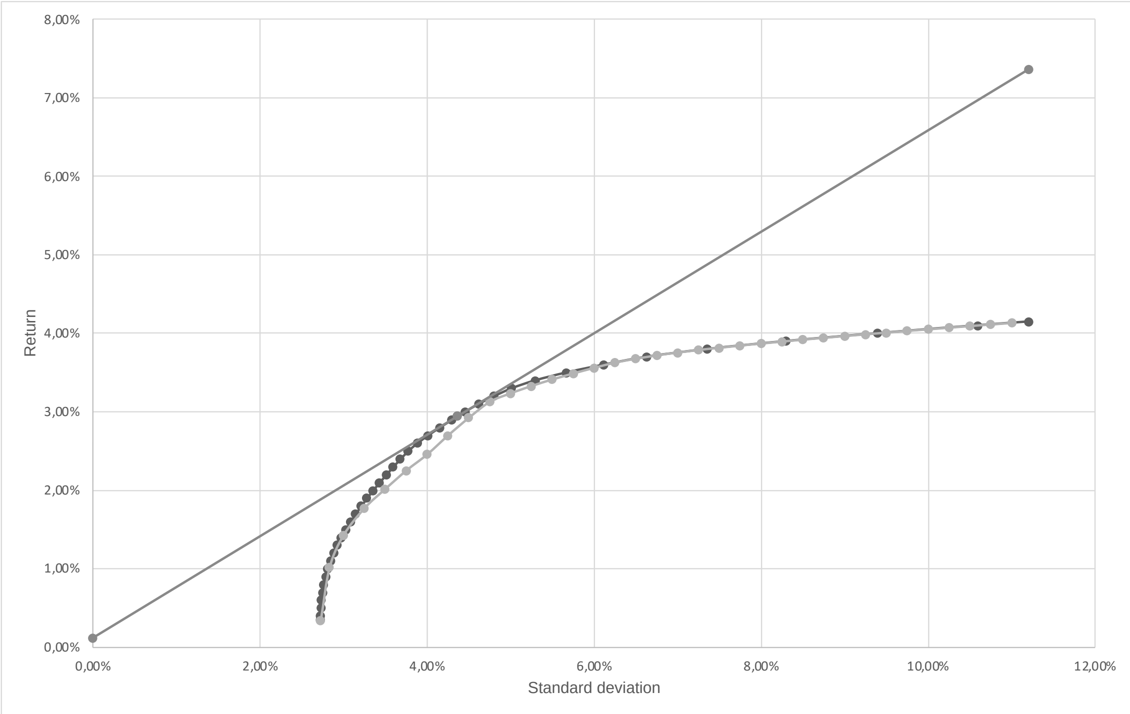
Table 5.5: Comparison table Mean-Variance and ESG Sharpe ratio - Standard deviation

	Portfolio MV	Portfolio ESG SR - SD
Return	3.63%	3.63%
Risk	6.25%	6.25%
Sharpe ratio	0.5612	0.5612
ESG risk rating	14.26	14.26

Source: Empirical analysis

Looking at Figure **5.5**, showing the Capital Allocation Line, the Mean-Variance, and the ESG SR - SD efficient frontiers translated into risk-return pairs, we can graphically observe what we have described. The maximum Sharpe ratio suggested by the third method is lower than that suggested by the first optimization method since the Capital Allocation Line does not intersect with the ESG SR - SD efficient frontier. Optimization through the latter implies that some portfolios will be inefficient when compared to the MV efficient frontier. In some cases, it implies portfolios with a slightly lower return for the same risk load. Optimization favors securities with a good ESG Sharpe ratio, but which will sometimes have a less attractive risk-return tradeoff.

Figure 5.5: Risk-return pairs of MV and ESG Sharpe ratio - Standard deviation optimizations



Source: Empirical analysis

Figure's legend:

Capital Allocation Line

MV risk - return pairs

ESG Sharpe ratio - SD risk return pairs

5.7 Final comparison between the three models

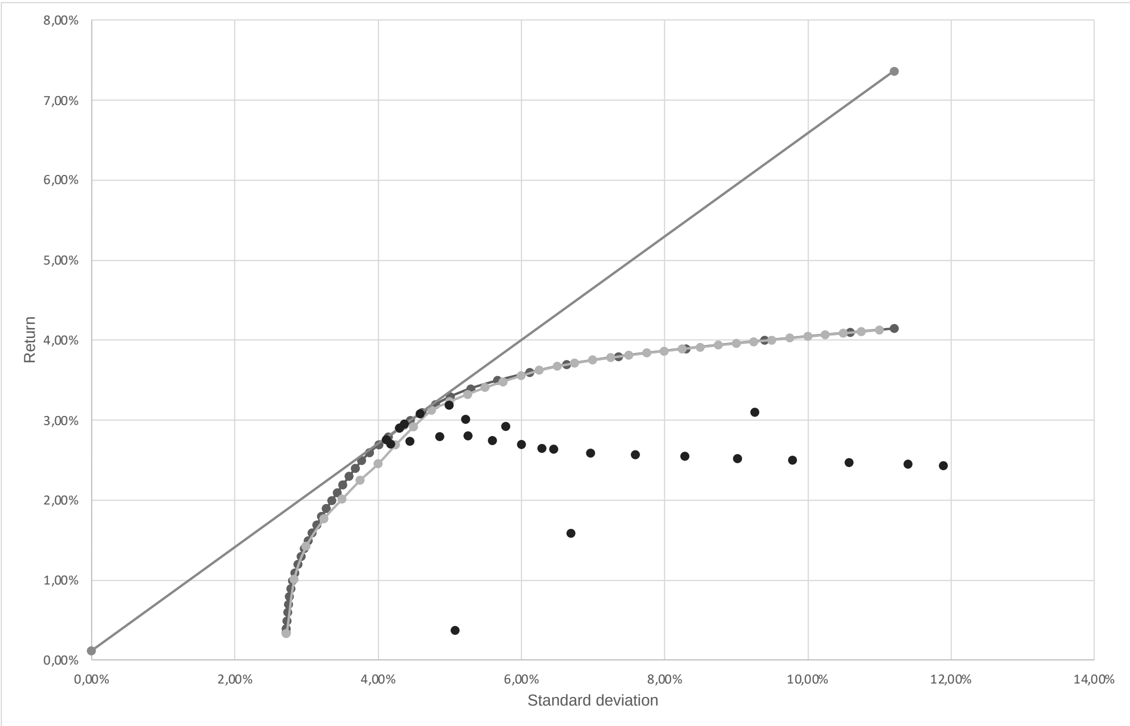
5.7.1 Comparison in the Mean-Variance framework

If we now integrate the SR - ESG risk rating and ESG SR - SD optimization into Modern Portfolio Theory, we notice that:

SR-ESG risk rating risk-return pairs are located on the MV efficient frontier around the tangent portfolio. This is normal as MV, and SR-ESG risk rating tangent portfolios are identical. Moreover, many pairs considered as efficient in the SR - ESG risk rating optimization are in fact below the MV efficient frontier. Optimizing on ESG risk ratings seems to be costly in terms of return and diversification in some cases.

In contrast to the SR - ESG risk rating pairs, the ESG SR - SD optimization proposes risk-return pairs that are identical in the tails with the MV efficient frontier. Optimizing with this new ratio initially indicates almost identical portfolios. Then, a gap appears as soon as we get closer to the MV tangent portfolio. The ESG SR - SD model favors return and ESG tradeoff. As a result, this model offers portfolios with a better ESG score but a poorer risk-return tradeoff and therefore a poorer Sharpe ratio. Finally, portfolios meet at the end of the efficient frontier (they have the same composition).

Figure 5.6: Capital Allocation Line, Mean-Variance risk/return pairs, Sharpe ratio - ESG risk rating risk/return pairs, and ESG Sharpe ratio - Standard deviation risk/return pairs



Source: Empirical analysis

Figure's legend:

Capital Allocation Line
MV risk - return pairs
SR - ESG risk return pairs
ESG SR- SD risk return pairs

5.7.2 Comparison in the SR-ESG risk rating framework

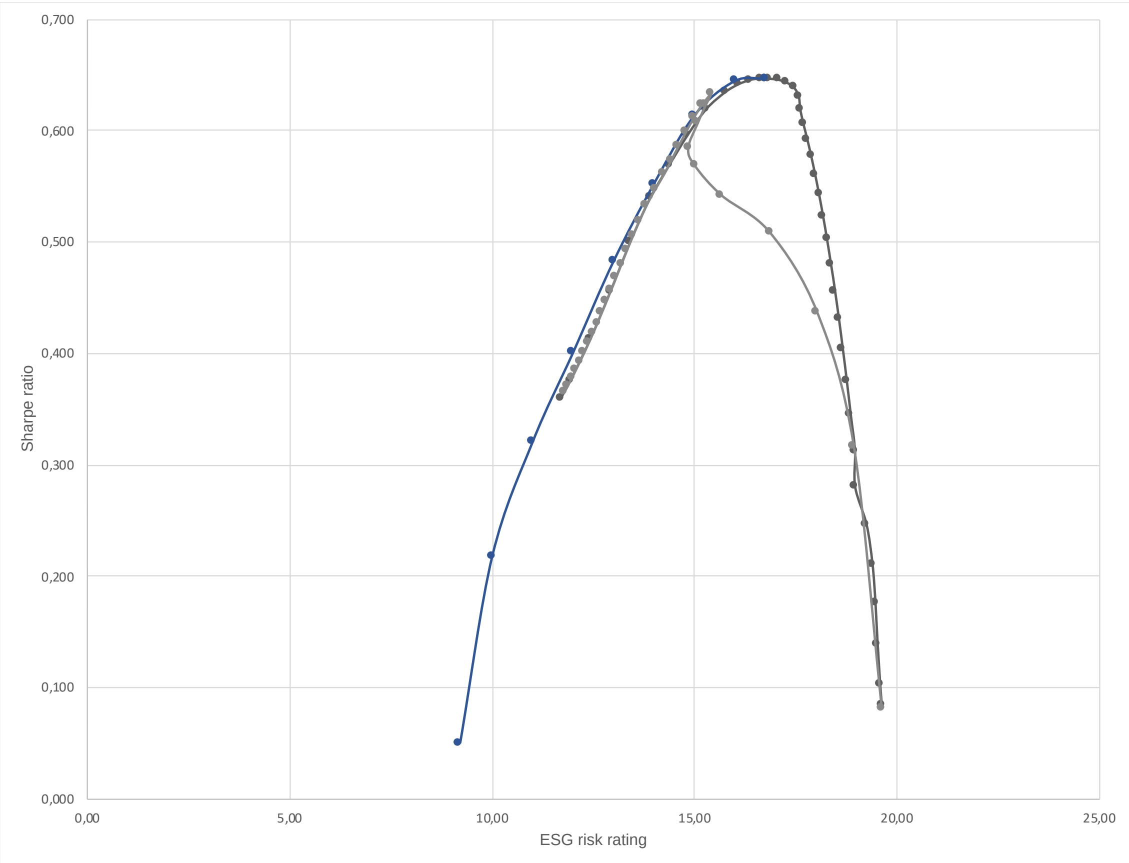
If we put the MV and ESG SR - SD optimization back into the SR - ESG risk rating optimization framework, we observe that:

As observed in Figure **5.7**, the SR - ESG risk rating optimization can create efficient portfolios with better ESG scores (up to a score of 11.70) than the other two optimizations but with lower Sharpe ratios.

The SR - ESG risk rating optimization proposes portfolios with the same Sharpe ratio, but with a smaller improvement in the ESG score compared to the other two models. The highest Sharpe ratio is proposed by both the MV model and the SR model - ESG risk rating model.

The ESG SR - SD optimization provides portfolios with identical Sharpe ratios to those offered by the MV model but with a much better ESG score. Therefore, the same Sharpe ratios are observed for different levels of ESG risk. However, the risk-return pairs are different (**cf. supra p.61**).

Figure 5.7: Sharpe ratio - ESG risk rating efficient frontier, Mean-Variance efficient frontier, and ESG Sharpe ratio - Standard deviation efficient frontier



Source: Empirical analysis

Figure's legend:

MV efficient frontier
SR - ESG risk rating efficient frontier
ESG SR - SD efficient frontier

6 Chapter: limits of the analysis and further improvements

This thesis and the analysis we have carried out understandably have some limits. These will be developed in the next section.

6.1 Limits of the analysis

6.1.1 Sustainalytics as provider

One of the limits of this analysis and these new optimization models is the fact that we only use ESG risk ratings from Sustainalytics as indicators of ESG performance. We have chosen to use the Sustainalytics score for several reasons.

Firstly, we wanted to use a "single" ESG score without combining it with other additional information that would have required further research. Combining ESG ratings with additional information is commonly used in the literature, as it provides a more accurate measure. (**cf. supra p.32**). Nevertheless, we wanted to propose an optimization model that was easy to use and quick to implement in institutions. Therefore, we decided to use a single provider.

Secondly, we have opted for Sustainalytics as it is one of the most used providers (Corporation 20/20, 2022; Finscience, 2020). Nevertheless, it is possible to criticize this choice. Other providers such as ASSET 4 or MSCI ESG would have been suitable and ESG profiles would have been different.

Thirdly, when looking at the literature more carefully, we note that criticisms made of Sustainalytics also apply to other providers. Indeed, the main issue is that there is no standardization of ESG scores. According to Lopez, Contreras, and Bendix (2020), there are some inconsistencies between scores assigned by rating agencies, and this leads to the inability of comparing companies. As a result, ESG scores designed to guide investors in their investment decisions can become confusing. This is because rating agencies measure items differently and have a different view on the materiality of the issue for example. Lopez *et al.,* (2020) believe that one of the major concerns with rating agencies is the lack of transparency about the methodologies applied. Not all agencies publish their methodology which makes it harder to understand. Lopez *et al.,* (2020) believe that there is an urgent need to standardize ESG scores. Moreover, they are convinced that providers should explain in detail considered dimensions and the processing of information.

Looking back at the methodology, Sustainalytics' methodology is subject to some criticism in comparison to those used by other large rating agencies. Using the research paper *Disagreement among ESG rating agencies: shall we be worried?* and the information published by rating agencies, we looked at the methodologies of the following providers: (1) Thomas Reuters ESG Scores, (2) MSCI ESG, (3) Robeco SAM, and (4) Sustainalytics to better understand where the differences come from and what aspects of Sustainalytics were valuable or could be improved. According to Lopez *et al.,* (2020), discrepancies between scores arise because rating agencies do not use the same variables, or because they apply different methodologies. After reviewing providers' methodologies, we were indeed somewhat surprised by the significant differences.

From our analysis, it seems to us that the methodology used by MSCI ESG is by far the simplest to understand and the most transparent. We observe some similarities with the Sustainalytics methodology as this rating agency also differentiates the company's exposure to risk and the company's management (**cf. supra p.23**). However, it only uses it for the Environmental (E) and Social (S) aspects as it considers that governance practices are manageable (Garz *et al.,* 2018; MSCI, 2022). MSCI ESG uses 3 pillars subdivided into 10 themes that address 35 ESG key issues. The final ESG rating corresponds to the weighted average of individual Environmental (E) and Social (S) ESG key issue scores. The Governance (G) pillar score is then computed and normalized to the peers (MSCI, 2022). Later, the weighted average of each underlying pillar score is computed and adjusted in comparison to the peer industry. Scores are then translated into final industry-adjusted scores and finally into an ESG rating. This methodology is therefore perhaps easier to understand because the notions of exposure and management are integrated from the beginning of the score calculations, which facilitates understanding. Moreover, fewer variables must be considered.

We also noted that Sustainalytics is the provider that makes the least use of a clear distinction between E, S, and G factors. In contrast, this distinction between the 3 factors is very present amongst other methodologies. The only exception is that the Robeco SAM score uses the notion of "Economic" instead of Governance. To some extent, this renders the methodology more straightforward and the allocation of weights to factors easier to understand (Garz *et al.,* 2018; MSCI, 2022; Robeco SAM, 2019; Thomson Reuters, 2017).

Furthermore, Sustainalytics scores are subject to a size effect. Indeed, it has been noted that large caps tend to have a better ESG score because they have better reporting and are generally more transparent. In practice, smaller companies have fewer resources to disclose non-financial information in a comprehensive and complete form (Garz *et al.*, 2018). As a result, Sustainalytics has introduced exposure to MEIs to substantially reduce the size bias. Although other providers do not refer to this issue in their methodologies, we can assume that they are also subject to this bias (Dumas, 2021). Rating agencies are blamed for issuing ESG scores that do not necessarily reflect reality. Nevertheless, it is important to consider that the formers use available data and that poor non-financial reporting leads to less accurate ESG scores (Sustainalytics, 2019). Indeed, this is one of the problems raised by Lopez *et al.,* (2020) in their research paper. They believe that there is a need to create a platform capable of gathering high-quality information accessible to all rating agencies. For example, companies would be required to enter their non-financial data. This kind of platform would help to reconcile scores and create greater credibility in the eyes of investors.

We can be critical of the choice to use the ESG risk rating given by Sustainalytics as its methodology has some weaknesses. Although scores are different, providers still agree on best-in-class and worst-in-class with a correlation of 0.95 (close to 1.0) which is a good sign (Lopez *et al.,* 2020). In addition, the Governance (G) factor has been identified in the literature (Lopez *et al.,* 2020; Pedersen *et al.* 2020) as the one with the greatest impact on the valuation, risk, and ESG profile of the company. Lopez *et al.*

(2020) note that all rating agencies agree that the G factor should be given greater weight, or at least treated in a particular way. This can also be noticed in Sustainalytics' methodology (**APPENDIX XIV: The building blocks of ESG risk ratings**).

The real issue is the choice of using only one score as an ESG performance indicator in the optimization model. Indeed, all methodologies are different and there are thus discrepancies between scores. This may indeed call into question the veracity and relevance of ESG profiles. Relying on a single ESG profile as a parameter for the optimization problem is risky, but at the same time, we wanted to propose an "investor-friendly " optimization model and the choice of a score from another rating agency could also have been subject to a thorough examination.

6.1.2 BEL20 as portfolio

The sample we have chosen as a portfolio to be optimized has limitations. First, it is very small as it contains 20 stocks. Hence, it does not represent the possible investment universe as it can be far larger. Second, we chose the representative index of the 20 largest market capitalizations in Belgium. Although these stocks are not required to be Belgian companies, most of them are. It is therefore a highly concentrated portfolio on the Belgian domestic market. It excludes securities from the United States or Asia, for example. In addition to that, ESG scores of the sample have a small spread. Perhaps some of the results would have been more revealing with a larger sample, composed of a wider range of industries. Furthermore, all assets are invested in equities. Funds and other asset classes are therefore completely excluded.

6.1.3 Timeframe

Another limit of this thesis concerns the time frame of the sample. As mentioned previously, it is not possible to retrieve historical Sustainalytics scores. Unlike volatility and return data, we were, therefore, unable to compute an average. Consequently, our optimization problem is only applicable as long as this ESG score is valid, and no event has affected the ESG profiles of BEL20 companies. In addition to that, the period over which historical prices were collected was strongly impacted by Covid-19.

6.2 Further improvements

In this part, we will look at the areas that could be improved and where this study could be further developed. The suggestions for further progress are related to the limits identified in the previous section.

6.2.1 Standardized ESG score

We investigated in detail the reasons why ESG scores assigned by rating agencies differed (**cf. supra p.63**). It is important to emphasize that if we had chosen another provider to collect data on ESG profiles, we would probably have obtained different eficient and tangent portfolios. This could discredit our research and our results. For this reason, we agree with Lopez *et al.*, (2020) that it would be appropriate to create standardized ESG scores and harmonize methodologies. In this way, all optimization problems would use the same data and there would be less risk of discrepancies. This would enhance the credibility of the models.

6.2.2 Utility function

As mentioned earlier (**cf. supra p.8**), one of the principles behind Modern Portfolio Theory is the utility function theorem. We explained in the previous section that this utility function is quadratic and that it allows us to identify investors' indifference curves based on two criteria: return and risk. By proposing a new optimization model that integrates ESG criteria, we were able to identify portfolios that provide the highest return for a minimum risk load. We also assumed where investors would fall according to their ESG preferences on the new efficient frontier (**cf. supra p.52**). Nevertheless, to enhance the model, it would be necessary to modify the utility function by including a new factor which has been already done in the literature (**cf. supra p.28**). In this way, it would be possible to identify the optimal portfolio for each investor according to his preferences. However, to propose such a utility function, it is necessary to identify and determine the factor that would quantify the ESG sensitivity of investors.

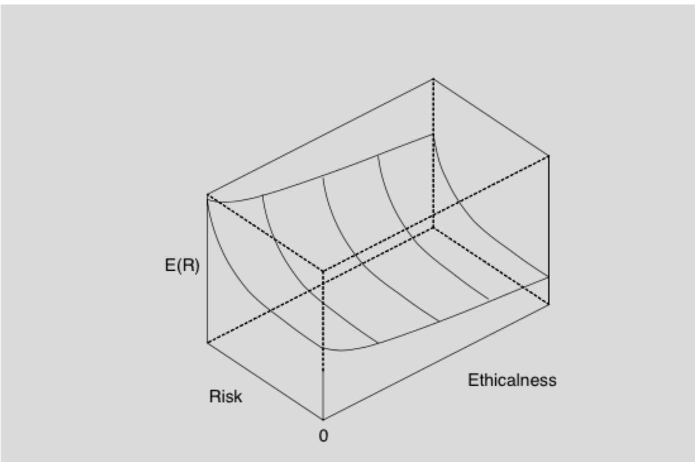
Pedersen *et al.*, (2020) were not the only ones to suggest modifying the utility function. Indeed, the pioneers of this idea are Beal *et al.,* (2005) as they explored the inclusion of ethical preferences in the utility function. Among the assumptions made by Markowitz in his model (**cf. supra p.10**), one of the strongest is that rational investors make their investment decisions solely based on risk and return. For example, they do not care about investing in companies that are not aligned with their ethical and social values. As a result, Beal *et al.,* (2005) explained that if one were to start from the approach developed in Modern Portfolio Theory, rational investors would invest in ethical securities if and only if these gave them a higher return for a lower or equal risk. However, Statman (2004) demonstrated that investors do not behave rationally and are influenced by other parameters such as their values, beliefs, history, etc. Given these elements, Beal *et al.,* (2005) added ethical preferences to the utility function. Indeed, ethical investments do not only provide a financial return but also a certain form of pleasure called "fun of participation". In this paper, the utility function, therefore, included 3 parameters: (1) expected return (E_R), (2) risk (σ_R), and (3) the degree of ethics of an investment (e).

$$U = f(E_R, \sigma_R, e) \tag{6.1}$$

Beal *et al.,* (2005) assumed that investors are willing to "accept diminished expected returns if the investment is more ethical (even if the risk-return trade-off for ethical investments is equivalent to those of ordinary investments)" (Beal *et al.,* 2005, p.21).

They arrived at an indifference map derived from the utility function. This 3D shape is due to the new three-parameters space.

Figure 6.1: Indifference Planes for a Range of Investor Types



Source: Beal, D. J., Goyen, M., et Philips, P. (2005). Why do we invest ethically? The Journal of Investing, 14(3), 66-78.

Beal *et al.,* (2005) were able to identify three classes of investors and behaviors from their sample. To begin with, they observed that investors who valued return, risk, and ethical considerations were willing to accept a tradeoff between these aspects. Then, they identified a segment of their sample who were not prepared to sacrifice returns for the ethical dimension of investing. If we look at Figure **6.1**, this class of investors would be on the front hedge. Finally, they identified the last category mainly composed of strong ESG-motivated investors such as NGO activists. These investors were not motivated by return or risk. They only considered the ethical aspect. For these investors, Beal *et al*., (2005) suggest that it might even be conceivable to remove risk and return from the utility function and only consider ethics.

The authors went even further in their analysis as they incorporated happiness into the model to place ethical investing in the utility function. Happiness is recognized as an experienced utility by researchers (Kahneman, Wakker, and Sarin, 1997; Kahneman, Krueger, Schkade, Schwarz and Stone, 2004)). The latter represents "the flow of pleasure (or displeasure) that the individual experiences whilst engaged in a particular activity" (Beal *et al.,* 2005, p.24).

$$u_i = \sum_j h_{ij}\mu_{ij} \tag{6.2}$$

$Where$
$h_{ij}\ is\ the\ amount\ of\ time\ an\ idividual\ i\ is\ engaged\ in\ a\ particular\ activity\ j$
$\mu_{ij}\ is\ the\ net\ affective\ experience\ of\ activity\ j$

The authors then assumed that in addition to this flow of pleasure, the individual also draws a utility from the expected return associated with the investment and disutility from the risk of the investment. According to the previous analysis, they expressed the utility derived from the investment by the following quadratic function:

$$u_i = (1+b)\,E_R + bE_R^2 - c\,\sigma_R^2 \tag{6.3}$$

$Where$

E_R $is\ the\ expected\ financial\ return$

σ_R^2 $is\ the\ variance\ of\ the\ security$

$b\ is\ a\ parameter\ ranged\ between\ -1\ and\ 0\ when\ investors\ are\ risk\ averse$

$c\ is\ a\ parameter\ ranged\ between\ 0\ and\ 1$

Using these two functions, they were able to reformulate the utility function U_i. They integrated the utility derived from an ethical investment into the utility function.

$$U_i = \sum_j h_{ij}\mu_{ij} + [(1+b)\ E_R + bE_R^2 - c\ \sigma_R^2] \qquad (6.4)$$

Beal *et al.,* (2005) went on to argue that, as they had previously concluded from the analysis of their investors' sample, the ethical part of the utility function can be removed if investors are unresponsive to this dimension. Their utility function would then become Function **6.3**. Similarly, if investors do not wish to lose financial performance at the expense of ethical considerations, then the utility function one would use would be the Function **6.3**.

Beal *et al.,* (2005) concluded that, just like the indifference curves of the classical model, an investor who must bear a higher risk load will want to obtain a higher return as a sign of compensation. Second, the "fun of participation" is positively correlated with the degree of ethics of the investment. The more ethical the investment, the more fun the investor will have. Conversely, if the investment is not socially responsible, then this will negatively impact the "fun of participation" and counterbalance the satisfaction derived from the financial return. This study and these conclusions are interesting for our research since indifference curves play an essential role in determining an investor's optimal portfolio.

Nevertheless, they highlighted the fact that even though they incorporated the ethical dimension into the utility function, it is still necessary to quantify investors' happiness derived from the ethical investment. This is what MiFID Sustainability attempts to do (**cf. supra p.18)**. However, Michael Van Den Spiegel (2022) explained that it was still very difficult to use this framework. Indeed, the legislation implements many items but has not fully developed a MiFID questionnaire yet. As of 2 August 2022, financial product distributors and advisors will have to ask clients to justify and clarify their ESG preferences (BNP Asset Management, 2022). However, as we have seen in the literature review, the implementation of MiFID Sustainability strongly depends on the introduction of other regulations. However, these regulations, such as the CSRD, should be enforced by 2024. This will make the task more difficult for distributors, asset managers, investors, and regulators (BNP Paribas Asset Management, 2022).

For the time being, financial institutions have the freedom to choose which questions will be used to determine investors' ESG preferences. There is no standardization yet, which can be an issue. When we interviewed Michael Van Den Spiegel (2022), he expressed his concerns about this new legislation. For example, we questioned him about the existence of a template questionnaire that could be used to capture the investor's ESG sensitivity, and he replied that there was no such questionnaire yet. Furthermore, he explained that the MiFID Sustainability questionnaire would be tightly linked to other legislation that was being implemented and there were loopholes in this area as well.

However, there are other avenues to measure investors' ethical sensitivity. Anand and Cowton (1993) attempted to incorporate ethical and social considerations into the utility function using the preferences of a sample of 125 ethical investors. To conduct their study, they used the EIRIS Services Limited database. This is a database of ethical investments located in London. For this study, 125 investors were asked to complete an Acceptable List Questionnaire (ALQ) by answering yes or no to a series of questions worded as follows: "Do you want to exclude...?" completed by a problematic sector of activity. The EIRIS database then used these answers and compiled them to propose companies that matched the investors' criteria.

6.2.3 Sample

We also mentioned that the selected sample was subject to some limits. For this reason, we believe that this new optimization model should be applied to another and more representative sample.

Furthermore, a question arises about the scores assigned to the securities in the sample. Our sample consists of 20 stocks that are all covered by the rating agency. Nevertheless, it is important to note that providers cover mainly equities and bonds as asset classes (since it is the issuer that is rated). Indeed, if the portfolio to be optimized is also made up of fund shares, it is not possible to find a score attributed by Sustainalytics or any other provider. One avenue that could be explored would be the nomenclature that is starting to be put in place by the European taxonomy. It consists of classifying funds into three main categories (Article 6, Article 8, and Article 9) according to their ESG impact (Mortier, 2021). Again, this means that there is still a lot of work to be done as the European taxonomy and classification of funds have not been harmonized yet. The decision-making power is currently in the hands of financial institutions and institutional investors (Ruelle, 2022) (**APPENDIX XVI: Semi-directed interview guide - Benoit Ruelle**).

6.2.4 Is ESG already included in the stock's standard deviation?

One question which would be worth investigating is whether ESG risk is already incorporated in the stock's risk measure. From our literature review and empirical study, we note that the volatility of the stock, i.e., its standard deviation, is calculated using historical data. Conversely, the ESG score is calculated not only from historical data (events, scandals, activities, etc.) but also represents the future ESG risk of the company. This score is therefore also based on a future component. However, if the ESG score was included in the company's risk, it would put its inclusion in Modern Portfolio Theory optimization problem in a different perspective.

Dunn, Fitzgibbons, and Pomorski (2018) were able to establish a correlation between a company's ESG profile and the risk it represents. They combined two databases (MSCI ESG and Barra's risk model) and found that the models were somewhat correlated. Stocks with a less robust ESG profile had a higher risk in the statistical models. They found that stocks with poor ESG exposure have an idiosyncratic risk that can be up to 15% higher than others. They also discovered that betas were up to 3% higher and that these stocks reacted slightly harder to the market. Although this finding does not reveal significant differences, it still demonstrates that ESG can provide additional information about the risk of an individual stock. As the magnitude is quite modest, this also implies that this risk is not particularly apparent in the short term but rather in the long-term. Hoepner, Oikonomou, Sautner, Starks, and Zou (2018) have also shown that ESG is correlated with risk. They concluded that ESG engagement reduces one of the downside risk factors. They explain that engagement (i.e., taking ESG considerations into account when investing) would reduce both idiosyncratic and systemic risk.

Dunn *et al.* (2018) explained that ESG considerations can therefore provide additional guidance to investors and are not only used for ethical purposes but there is little research on this subject. It would therefore be interesting to study in further detail the relationship between risk and the ESG score of securities.

Conclusion of the empirical work

As a reminder, the research objective of this thesis was to propose an optimization tool based on Modern Portfolio Theory and capable of integrating ESG criteria. Using our empirical study, we were able to answer our research question. We were interested in finding a way to integrate the ESG criteria into the Mean-Variance framework and to observe the impact of this new constraint on the efficient frontier as well as on the tangent portfolio.

We formulated two assumptions (**cf. supra p.40**) as we imagined two different optimization models (SR-ESG risk rating and ESG SR - SD). After our empirical analysis, we can confirm the first hypothesis and refute the second one.

Indeed, if we first focus on the SR - ESG Sharpe ratio optimization model, we observe that the efficient frontier has shifted to the right as the x-axis no longer represents the standard deviation, but the ESG score instead. The portfolio with the lowest ESG score is the portfolio fully invested in GBL, the company with the lowest ESG score (9.2). The frontier has indeed adopted a concave shape since, unlike the MV optimization, the SR-ESG risk rating model proposes portfolios with an ESG score up to 32.6 (i.e., the score of the worst ESG company in the BEL20). The new efficient frontier shows that improving the ESG score of the portfolio is costly in terms of risk-adjusted return. Moreover, if we put the SR-ESG risk rating optimal portfolios back into the MV framework, we observe that most of the pairs are inefficient (except those close to the tangent portfolio) according to the definition given by Modern Portfolio Theory. This is because we use an ESG score as a constraint while optimizing on the Sharpe ratio. We also observe that the composition of the tangent portfolios provided by the MV, and the SR-ESG risk rating models are identical. This is in line with the findings observed in the literature (Pedersen *et al.*, 2020; Mercereau and Melin, 2020).

Furthermore, we can refute the second hypothesis which relates to the ESG SR-SD optimization model. The efficient frontier is similar in shape to the classical efficient frontier. Moreover, we expected something much flatter due to the modification of the Sharpe ratio with the ESG risk as the denominator. The frontier has not shifted to the right as we continued to use the standard deviation as the x-axis. As far as the tangent portfolio is concerned, it should be highlighted that maximizing the ESG SR ratio while applying a constraint on the standard deviation proposes a lower optimal portfolio than the MV optimization. This is consistent with what Mercerau and Melin (2020) and Garcià *et al.,* (2019) observed in their research. Taking the ESG into account to determine the tangent portfolio in this model implies a deterioration of the Sharpe ratio. Securities in the MV optimal portfolio with a lower ESG score are therefore removed from the portfolio and the weighting in the remaining securities is increased. This reduces the diversification phenomenon. What we have just explained can also be observed by replacing the risk-return pairs of the efficient frontier ESG SR - SD in the universe of Modern Portfolio Theory (Figure **5.5**).

General conclusion

Using this thesis information and evidence collected from scientific and professional sources, we identified an area in finance that deserved to be further investigated. Indeed, a clear mismatch has been established between the theory used in portfolio management and the current trend towards which the financial world heads. Both individual investors and large financial institutions show interest in sustainable finance. Regulations also shift towards more ethical and transparent finance. We wanted to make a small contribution to this overall context.

We have attempted to align Modern Portfolio Theory, unchanged for 70 years, with Socially Responsible Investment. To this end, we proposed two optimization models capable of integrating ESG criteria into the Mean-Variance framework.

The SR-ESG risk model allows investors to identify portfolios for a certain ESG score with the maximum Sharpe ratio. Investing in some of these portfolios would not always be rational since it is possible to obtain for the same Sharpe ratio, a portfolio with a better ESG score (represented by the right side of the SR-ESG risk rating tangent portfolio, as observed in Figure **5.7**). This model is inspired by and similar to the ESG-efficient frontier developed by Pedersen *et al.*, (2020). Most of these SR-ESG risk rating risk-return pairs are not efficient in Modern Portfolio Theory. Furthermore, optimizing based on the Sharpe ratio can be misleading as generally two investments are compared with respect to Sharpe ratios if they have an equivalent return or risk. Consequently, it is important to be aware of the two parameters used in this new optimization.

The ESG SR - SD model allowed to identify the portfolios with the best ESG Sharpe ratio for a certain risk level (σ). Our findings confirm once again what had already been established in the literature (Gasser *et al.*, 2017; Garcià e*t al*., 2019; Mercerau and Melin, 2020). Portfolios on the efficient frontiers are identical in the tails (in terms of composition). However, there is a spread when approaching the tangent portfolio. Consequently, it seems that taking ESG into account bears costs in terms of risk-return tradeoff, therefore, leading to a deterioration of the Sharpe ratio. In this area, the securities in the MV tangent portfolio with poorer ESG scores are replaced by higher weights in the healthier securities for the ESG SR - SD portfolio. We are also conscious that this optimization may be more challenging to interpret as we use a derivative of the Sharpe ratio.

We believe it is important to understand the parameters used in these two new models. The Sharpe ratio is used extensively as a comparative tool. However, just because two portfolios offer the same Sharpe ratio does not mean they provide the same return. It is only a measure of risk-adjusted return to assess how much return is obtained in relation to the risk taken.

This thesis contributed to the literature for several reasons. First, the integration of the ESG criteria into the Harry Markowitz model has not yet been fully explored. There are a limited number of articles available on this subject. Moreover, the optimization based on a modified Sharpe ratio to consider ESG has never been done to our knowledge. We innovated this subject by proposing this new optimization model. This paper also highlights limitations that have not been underlined by other research. We refer to the need of using standard ESG scores or the need to measure investors' sensitivity to ESG.

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