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ESG compliant optimal portfolios:
The impact of ESG constraints on portfolio optimization in a sample of European stocks*

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Abstract

The introduction of the Environmental, Social, Governance (ESG) dimensions in setting up optimal portfolios has been becoming of uttermost importance for the financial industry. Given the absence of consensus in empirical literature and the limited number of studies providing performance comparison of ESG strategies, the aim of this paper is to assess the impact of ESG on optimal portfolios and to compare different approaches to the construction of ESG compliant portfolios.
Following Varmaz et al. (2022) optimization model, we minimize portfolio residual risk by imposing a desired level of portfolio average systemic risk and ESG (measured by Bloomberg ESG score) over both an unscreened and a screened sample based on the 586 stocks of the EURO STOXX Index in the period January 2007 – August 2022.
Three are the main results. First, regardless of the level of portfolio systemic risk, the Sharpe ratio of the optimal portfolios worsens as the target ESG level increases. Second, the Sharpe ratio dynamics of portfolios with the highest average ESG scores follows market phases: it is very close to/higher than other portfolios in bull markets, whereas it underperforms in stable or bear markets suggesting that ESG portfolios do not seem to represent a safe haven. Third, negative screenings with medium-low threshold reduce the performance of optimal portfolios with respect to optimization over an unscreened sample. However, when adopting a very severe screening we obtain a superior performance implying that very virtuous companies allows investors to do well by doing good.

Keywords: sustainable portfolio, portfolio optimization, investor preferences, ESG score, negative screening, portfolio performance

J.E.L. classification: C61, G11, M14, Q01

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1. Introduction

In recent years, investors' attention towards environmental, social and governance (ESG) dimensions has significantly increased spurred by UN initiatives and programs (e.g. the 2030 Agenda and the Principles for Responsible Investment; PRI, 2017) and historical events. For instance, crises have played an important role in raising investors' awareness towards social responsibility and sustainability issues, in fact global financial crisis of 2007-2008 highlighted the importance of corporate social responsibility (Cesarone et al., 2022), while Covid-19 pandemic has made sustainability a priority instead of a luxury good (Pástor and Vorsatz, 2020). Hence, sustainable investments have become central also in asset allocation and asset managers integrate these non-strictly financial aspects into their investment policies (van Duuren et al., 2016). According to the Global Sustainable Investment Review (GSIA, 2021) asset under management reached USD 35.3 trillion in 2020, (growing by 15% in two years) and they represent 36% of all professionally managed assets across the major markets (Europe, United States, Canada, Australasia and Japan). Primarily than obtaining a financial return, sustainable investors incorporate ESG assets in their portfolio to hedge specific risks such as climate risk (e.g. Engle et al., 2020; Alekseev et al., 2022) or simply to contribute to a better society and to promote good corporate behaviour (Pedersen et al., 2021).

The literature has investigated several strategies according to which investors can set up socially responsible and ESG portfolios: from screening strategies and a combination of the latter with traditional portfolio theory to optimization problems that extend the mean-variance optimization model by considering a sustainability dimension beside risk and return. However, the existing literature is inconclusive about the relation between optimal portfolio ESG score and its financial performance. Moreover, it has given little attention to the comparison of different strategies and has usually proposed models that require balanced datasets.

The aim of this paper is twofold: first, we provide a review of the literature on the existing approaches to include the ESG dimensions into portfolio optimization; second, we contribute to the literature with an original piece of research. To this latter end, we investigate the setup of optimal portfolios for ESG assets by providing answers to two main research-questions that motivate our work: Are optimal portfolios with a high ESG score penalized by a lower financial performance? Does optimal portfolio performance deteriorate when we focus on a negatively screened sample instead of an unscreened one?

As far as we know, this is one of the first studies adopting the innovative model by Varmaz et al. (2022) that allows us to determine the optimal portfolio that minimizes residual risk for a given level of systemic risk and ESG score. It has technical and practical advantages and it does not require the estimation of the covariance matrix, so it is suitable also when data are represented by an unbalanced panel. The latter characteristic is particularly relevant in empirical implementation since it allows including in their portfolio investment set also stocks with shorter time series. We set up optimal portfolios starting from the 586 stocks that composed the EURO STOXX Index in the period January 2007 – August 2022 and we approximate the ESG characteristic by means of the Blooomberg ESG disclosure score, which assess firm's transparency on ESG issues. Then, in order to compare our results with the most used portfolio strategies (i.e. screening strategies; see for instance Auer (2016), Bertelli and Torricelli, 2022), we solve the model also over a negatively ESG screened sample.

Three are the main results. First, regardless of the level of portfolio systemic risk, the Sharpe ratio of the optimal portfolios is negatively related to the level of the ESG constraint.

Second, the Sharpe ratio of portfolios with the highest average ESG scores (i.e. 50 and 60) shows a dynamics that follows market phases: it is very close to/higher than the Sharpe ratio of other portfolios during bull market phases, whereas underperforms in constant or bear market phases.

Third, when we adopt a negative ESG screening strategy with medium-low threshold, the optimization model suffers of a general reduction in the performance with respect to an optimization over an unscreened sample. However, we obtain a superior performance when adopting a very severe screening, a result underscoring that, by considering only the most virtuous companies, investors can do well by doing good.

The paper is organized as follows. Section 2 provides a critical review of the theoretical and empirical literature on ESG compliant portfolio approaches. Section 3 illustrates the analytics of the optimization model we adopt to provide an original contribution and Section 4 illustrates the dataset used. Section 5 presents the empirical methodology, Section 6 discusses results on optimal portfolio performance. Last Section concludes.

2. An overview of ESG compliant portfolio approaches

The literature on ESG related portfolios has its roots in the literature on socially responsible investing (SRI) and has been growing very fast in the latter years spurred by the availability of scores and rating useful to evaluate companies' nonfinancial performance in consideration of environmental, social and governance (ESG) factors.

There are several strategies, characterized by different levels of complexity and sophistication, through which investors and asset managers set up socially responsible and ESG portfolios: from screening strategies and a combination of the latter with traditional portfolio theory to optimization problems that consider the sustainability dimension beside risk and return. These strategies essentially characterize three main strands of literature that are discussed in the following paragraphs.

2.1. Screening strategies

A first strand of literature proposes a strategy, widely used in practice because of its simplicity, that consists of implementing some sort of screening on the investment set. Negative screening excludes assets according to some socially responsible criterion such as excluding companies or sectors involved in immoral activities or characterized by low ESG measures, while positive screening tilts portfolio towards assets belonging to outperforming companies in terms of social responsibility or sustainability. When positive screening implies the selection of most virtuous companies relative to industry peers, it is referred to as best-in-class. As for the sort of screening, two are the main approaches taken. In the early literature, socially responsible investing consisted mainly in the exclusion of the so-called "sin stocks" i.e. stocks belonging to sectors considered unethical or immoral such as tobacco, alcohol, gambling and weapons (Blitz and Fabozzi, 2017; Hong and Kacperczyk, 2009). Later on, with the introduction of ESG scores and ratings by different agencies, screening is achieved by the exclusion (selection) of assets associated to low (high) scores and by equally weighting the survived (selected) assets. An alternative to equal weights consists in using weights resting on market capitalization. However, the literature is inconclusive about the impact of ESG criteria on financial portfolio performance. Although socially responsible firms could potentially benefit from higher profitability (Friedman, 1970; Bénabou and Tirole, 2010), empirical studies do not always find an overperformance associated to ESG portfolios with respect to a passive benchmark. For instance, Auer (2016) applies ESG screenings by using Sustainalytics scores over the components of the STOXX Europe 600 index in the period 2004-2012 and finds that only screenings based on the governance dimension realize a better performance with respect to the benchmark index. Bertelli and Torricelli (2022) implement negative and positive screening strategies using Bloomberg ESG scores and the EURO STOXX index. They prove overperformance of negative screening strategies over the long term (2007-2021) and non-overperformance of screened portfolios during periods of crisis such as the global recession and Covid-19 pandemic. Alessandrini and Jondeau (2020) show that negative screenings based on ESG scores on MSCI ACWI Index over the period 2007-2018 improve the overall ESG score of the resulting portfolios without reducing their risk-adjusted performance.

2.2. A two-step approach: traditional portfolio optimization over a screened sample

A second strand of literature, takes a different approach resting on the idea of separating the ESG decision from the portfolio construction (Bender et al., 2017). According to this approach the first step is the ESG screening over the constituents of a diversified index, the second is the set up an optimal portfolio problem with the survived assets (Markowitz, 1952). Hence, the ESG issue is taken into consideration at the screening level of the investment set, over which a conventional optimal portfolio problem is solved in order, for example, to minimize portfolio risk or the tracking error. With respect to pure-screening strategies, which use simple weighting techniques, these strategies allow the investor to meet financial objectives beside ESG ones, even if some trade-offs still emerge as demonstrated by Bohn et al. (2022). Starting from the MSCI ACWI Index, they implement negative screening and adopt two different strategies: a Simple Exclusion by cap-weighting the survived stocks and an Optimized Exclusion by weighting the survived securities to minimize forecast tracking error to the benchmark. Optimized Exclusion results in a portfolio that on one hand mimics the benchmark, but on the other it assigns higher weights to stocks correlated with the excluded ones and potentially just as undesired, however, its Information Ratio is higher than the one of the Simple Exclusion. Liagkouras et al. (2020) first perform a screening over the constituents of FTSE-100 index in order to exclude assets that do not respect the ESG constraint, then set up optimized portfolios based on a mean-variance portfolio optimization model. They find that the optimal allocation of assets with high ESG score is characterised by a worse risk-return combination than optimized portfolios of the unscreened sample, therefore they conclude that ESG investors must be ready to sacrifice a part of their wealth. Similarly, Wang et al. (2022) show that screening, based on Bloomberg scores, reduces minimum variance portfolio performance in the Chinese stock market. In sum, the initial screening introduces constraints on the investment set that limits portfolio diversification and profitability according to traditional portfolio theory (Markowitz, 1952; Girard et al., 2007; Ortas et al., 2014).

2.3. Portfolio optimization including the ESG dimension

A third strand of literature, which aims to overcome the drawbacks of screening, proposes to address the optimal portfolio problem by including the ESG dimension beside risk and return over an unscreened sample. It results in an extension of the two-dimensional Markowitz optimization problem to a tri-criterion portfolio selection model that includes an additional linear objective (for instance ESG) to the portfolio mean and variance objectives (Hirschberger et al., 2013; Utz et al., 2014; Cesarone et al., 2022). The socially responsible dimension can be represented by several measures: most studies use an aggregate ESG score or rating provided by different agencies (e.g. Refinitiv, Thomson Reuters, MSCI, Sustainalytics); but the focus could be also on a single dimension such as greenhouse gas (GHG) emission intensity (De Spiegeleer et al., 2021). Utz et al. (2014) propose one of the first models that explicitly considers the ESG dimension and by means of an inverse optimization process they investigate how assets are allocated in socially responsible mutual funds. Their findings suggest that, apart from an initial screening, there are not significant differences in the asset allocation of SR and conventional mutual funds; moreover, SR mutual funds are not characterized by a higher ESG score. Cesarone et al. (2022) adopt a mean-variance-ESG model to set up optimal portfolios for five different datasets representing indexes from major stock markets (Dow Jones Industrial, Euro Stoxx 50, FTSE100, NASDAQ100, S&P500) over the past 15 years. Over the full period, from 2006 to 2020, high-ESG portfolios show a better financial performance only in the US markets, whereas in the subperiod 2014-2020, after the Kyoto Protocol, a higher performance is recorded in four out of five datasets. Gasser et al. (2017) revised the traditional Markowitz's model and find that investors face a decrease in the Sharpe ratio when setting up optimal portfolios with high social responsibility. Moreover, given that risk and return can be synthetized by the Sharpe ratio, the optimization problem across three dimensions (risk, return, ESG) can be reduced to a trade-off between ESG and Sharpe ratio (Pedersen et al., 2021) or ESG tilted Sharpe ratio (Schmidt, 2022). In this connection, Pedersen et al. (2021) derive an ESG-Sharpe ratio frontier showing that increasing the ESG characteristic of the portfolio leads to a drop in the Sharpe ratio and that the frontier for investors who apply negative screens on asset with low ESG score is dominated by the unconstrained one. Finally, Alessandrini and Jondeau (2021) propose a model that maximizes portfolio ESG score by imposing restrictions on the tracking error, transaction cost, and risk exposures, and they find that investors can improve the ESG quality of their portfolio without sacrificing risk-adjusted performance.

The above-mentioned studies dealing with ESG optimization assume that ESG features have an effect on portfolio return because they modify portfolio exposure to systemic risks. However, another approach within this third strand of literature assumes that assets with high ESG scores realize an additional expected return that is unrelated to assets' systemic risk (e.g. Bénabou and Tirole, 2010; Edmans, 2011; Friede et al., 2015; Hoepner et al., 2021). In this regard, Varmaz et al. (2022) provide a relatively simple new optimization model that overcomes some issues in the traditional mean-variance optimization (i.e. the estimation of the covariance matrix and the identification of investors' return, risk and ESG preferences) and is flexible to accommodate the two competing approaches about ESG dimensions: ESG affecting portfolio returns by means of systemic risk and ESG affecting portfolio returns only.

In sum, in recent years there has been a strong development in optimization models considering the ESG dimension, but previous studies have not reached a consensus regarding the relation between portfolio performance and ESG score. Further, only few studies compare the financial performance of optimal portfolios resulting from different strategies (e.g. tri-criterion optimization or strategies that apply screenings before the optimization process). Finally, traditional optimization models need balanced panels to be implemented, therefore in their application only market indexes or stocks with long time series are considered.

3. The analytics of the optimization model

Since we aim to investigate the ESG impact on portfolio performance by means of an innovative model that allows investors to choose among a wide asset universe consisting of also recently listed assets, we adopt the model by Varmaz et al. (2022) that provides an analytical solution without the need of estimating the variance-covariance matrix, and thus it is suitable also in presence of unbalanced panels. In addition, we test the approach by Varmaz et al. (2022) over both an unscreened and a negatively screened sample in order to explore the effect of screenings on the performance of optimal portfolios.

In this section we describe the optimization model that we use to set up ESG portfolios. In Section 3.1., starting from a traditional mean-variance optimization framework, we show how the literature agrees to extend it by accounting for the ESG dimension; then in Section 3.2. we present the innovative model proposed by Varmaz et al. (2022) that brings technical advantages in the construction of an optimal ESG portfolio.

3.1. ESG in mean-variance optimization

According to Markowitz (1952), risk-averse investors seek the portfolio that maximizes the expected return and minimizes the variance. Hence, considering N risky assets, we recall the classical mean-variance portfolio optimization model:[1]

$$\max_{w} \quad \alpha\mu_P - \frac{1}{2}\lambda\sigma_P^2 \tag{1}$$
$$\text{s.t.} \quad w^T 1 = 1$$

where:

w = $N \times 1$ vector of portfolio weights;

α = scalar that represents investor's return preference;

μ_P = portfolio expected return calculated as $w^T\mu$ where μ is an $N \times 1$ vector of expected asset excess returns;

λ: a scalar that represents investor's risk preference;

σ_P^2 = portfolio return variance calculated as $w^T V w$ where V is an $N \times N$ positive semidefinite variance-covariance matrix of asset returns.

[1] Markowitz's problem can be represented in a mean-variance plane because it assumes that investors select portfolios exclusively on the basis of the expected return and the expected variance of asset returns. This assumption is supported either by normally distributed returns (for any expected utility function) or by a quadratic utility function (for any return distribution), which represents risk-averse individuals (for more details see e.g. Ricci and Torricelli (1992), Chapter 5).

Because of investors' preferences for sustainable investments (Rossi et al., 2017; Hong and Kacperczyk, 2009) the model (1) can be extended by incorporating ESG beside market risk and return (Varmaz et al., 2022; Cesarone et al., 2022; Pedersen et al., 2021; Utz et al., 2014; Gasser et al., 2017). As previous studies we assume the additivity of the ESG dimension in line with Drut (2010). It results in the following tri-objective optimization problem:

$$\max_{w} \quad \alpha\mu_P - \frac{1}{2}\lambda\sigma_P^2 + \epsilon\theta_P \qquad (2)$$
$$\text{s.t.} \quad w^T 1 = 1$$

where:

ϵ = scalar that represents investor's ESG preference;

θ_P= portfolio ESG score calculated as $w^T\theta$ where θ is an $N \times 1$ vector of asset ESG scores.

Problem in (2) can be rewritten as the maximization of the Lagrange function:

$$\max_{w} \Lambda: \quad \alpha\mu_P - \frac{1}{2}\lambda\sigma_P^2 + \epsilon\theta_P - h(\, w^T 1 - 1) \qquad (3)$$

where h is the Lagrangian multiplier and the solution for optimal weights is given by:

$$w = \frac{\alpha}{\lambda}V^{-1}\mu + \frac{\epsilon}{\lambda}V^{-1}\theta + \frac{h}{\lambda}V^{-1}1 \qquad (4)$$

The problem in (2) and its solution (4) take μ, V and θ as parameters that can be estimated from the data, whereas the parameters α, λ and ϵ must be specified a priori consistently with investors' preferences. However, investors might encounter some difficulties in quantifying their preferences with α, λ and ϵ because they are not directly observable. Rather, it is easier for investors to express their desired levels for portfolio return, risk and ESG score respectively as follows:

$$\mu_P^* = \mu^T w \quad ; \quad \sigma_P^{2*} = w^T V w \quad ; \quad \theta_P^* = \theta^T w \qquad (5)$$

By substituting the optimal solution (4) into objective properties of the portfolio (5) there is a one-to-one correspondence between desired portfolio characteristics and α, λ, ϵ parameters. The latter can be derived by solving a three-equation system with three unknowns, because investors desired portfolios must be consistent with parameters preferences so that they lead to the same optimal solution for w. Based on this correspondence and in line with Varmaz et al. (2022) the approach in

(2) can be reformulated by setting the desired levels of portfolio return and ESG score as linear equality constraints of the optimization program that aims to minimize portfolio variance:[2]

$$\begin{aligned} \min_{w} \quad & \frac{1}{2} w^T V w \\ \text{s.t.} \quad & w^T 1 = 1 \\ & w^T \mu = \mu_P^* \\ & w^T \theta = \theta_P^* \end{aligned} \tag{6}$$

The resulting optimal portfolio is a minimum variance portfolio laying on the efficient frontier that has exactly the desired level of return and ESG score as determined by investors' preferences. Moreover, by setting investors' desired portfolio characteristics (μ_P^* and θ_P^*) consistently with their preferences α and ϵ, both programs in (2) and (6) bring to the same optimal portfolio weights. This can be demonstrated by calculating the Lagrangian function of equation (6) and comparing its solution to the one represented by equation (4). The Lagrangian function is:

$$\min_{w} \Lambda: \quad \frac{1}{2} w^T V w - x(w^T 1 - 1) - y(w^T \mu - \mu_P^*) - z(w^T \theta - \theta_P^*) \tag{7}$$

with x, y and z as Lagrangian multiplier and the corresponding solution is:

$$w = xV^{-1}\mu + yV^{-1}\theta + zV^{-1}1 \tag{8}$$

and by setting $x = \frac{\alpha}{\lambda}$, $y = \frac{\epsilon}{\lambda}$ and $z = \frac{h}{\lambda}$ it equals the solution in (4).

3.2. The model by Varmaz et al. (2022)

Starting from the problem in equation (6) Varmaz et al. (2022) propose a further reformulation that brings both technical and practical advantages in the incorporation of ESG into mean-variance optimization.

They start by assuming the validity of a single-factor model for asset returns and that the ESG dimension, for instance the ESG score of a stock, can affect the return of the stock itself without affecting the covariance structure among assets.[3] This vision is supported by both theoretical (Bénabou and Tirole, 2010) and empirical (Edmans, 2011; Friede et al., 2015) literature. Hence an

[2] With respect to equation (2), expected return and ESG score are considered in the constraints and only portfolio variance remains in the maximization function. The maximization of $-\frac{1}{2}\lambda\sigma_P^2$ corresponds to the minimization of $\frac{1}{2}w^T V w$.

[3] Varmaz et al. (2022) demonstrate that the model can be easily extended in order to accommodate more risk factors and also an ESG risk factor coherent with the theory (e.g. Pástor et al., 2021; Pedersen et al., 2021) that ESG can lead to a factor risk premium affecting returns. At this stage of the analysis we consider a single-factor model and the theory according to which ESG can be seen as a characteristic affecting return without translating into more/less risk. Moreover, in the example proposed by Varmaz et al. (2022) there is a quite high correlation (-35%) between the market risk factor and the ESG risk factor.

asset expected return can be described as a liner function of the factor loading (beta) on the market risk factor and of the ESG characteristic (e.g. ESG score or rating):

$$E(R_{i,t}) = \beta_i(E(R_{m,t})) + \theta_i c \tag{9}$$

where:

$R_{i,t}$ = excess return of asset i at time t;

$R_{m,t}$ = excess return of the market portfolio at time t, i.e. the market factor;

β_i = sensitivity of asset i return to the market factor, calculated as $\frac{cov(R_i,R_m)}{\sigma_{Rm}^2}$ with σ_{Rm}^2 that represents the excess return variance of the market portfolio;

θ_i = ESG characteristic of asset i;

c = estimated reward for the ESG characteristic.

We have to recall that according to the CAPM (Sharpe, 1964; Lintner, 1965; Mossin, 1966), and more generally to a single-index model, portfolio variance can be rewritten as a function of market risk and residual risk (residual variance):

$$\begin{aligned} \sigma_P^2 &= w^T V w \\ &= w^T(\beta\sigma_{Rm}^2\beta^T + RV)w \end{aligned} \tag{10}$$

where RV (residual variance) is a diagonal $N \times N$ matrix of the unsystematic part of asset i variance ($\sigma_{\varepsilon i}$), because asset i residual risks (ε_i) are assumed to be i.i.d.

Therefore, Varmaz et al. (2022) propose to simplify the model in (6) by introducing a constraint about investor desired portfolio beta β_P^* that, together with portfolio desired ESG score θ_P^* and according to the factor model in (9), determines portfolio desired level of return μ_P^*. Moreover, portfolio beta does control for the first summand in equation (10) i.e. market risk. Hence, by introducing a constrain about the desired portfolio beta, the objective function of equation (6) reduces from total risk to residual risk only. Such residual risk (RV) is a diagonal matrix that can be eliminated without changing the result of the optimization problem that becomes as follows:

$$\begin{aligned} \min_{w} \quad & \frac{1}{2} w^T w \\ \text{s.t.} \quad & w^T 1 = 1 \\ & w^T \beta = \beta_P^* \\ & w^T \theta = \theta_P^* \end{aligned} \tag{11}$$

The final optimization problem in (11) aims at minimizing residual risk by setting a desired level of portfolio beta and ESG score in line with investors' preferences. A more compact representation is

$$\min_{w} \quad \frac{1}{2} w^T w \qquad (12)$$
$$\text{s.t.} \quad X^T w = b$$

where:

$X = [1, \beta, \theta]$, a $N \times 3$ matrix that gathers the variables on the left-hand side of the constraints of (11);
$b = [1, \beta_P^*, \theta_P^*]^T$, a vector that gathers the variables on the right-hand side of the constraints of (11).

We can then define the following Lagrangian function with k^T representing the 1×3 vector of the Lagrange multiplier:

$$\min_{w} \Lambda: \quad \frac{1}{2} w^T w - k^T (X^T w - b) \qquad (13)$$

The solution differs across investors, because they have individual preferences for the desired values in vector b, and is represented by equation (22):

$$w^T = b^T (X^T X)^{-1} X^T \qquad (14)$$

Problem in (12) is reported without specifying the subscript t indicating a precise moment in time, but it can be solved for each time period in our sample retrieving a vector of optimal weights. We are then able to compute the out-of-sample realized returns R_t of the portfolio at time t

$$R_t = w_{t-1}^T r_t = b^T (X_{t-1}^T X_{t-1})^{-1} X_{t-1}^T r_t \qquad (15)$$

The model proposed by Varmaz et al. (2022) presents four main advantages with respect to the traditional mean-variance approach and its extension to incorporate ESG. First, by eliminating the portfolio variance from the objective function and by setting only equality constraints, it reduces the computational complexity of the problem and brings to an analytical solution.[4] Second, the model does not require the estimation of expected returns and the variance-covariance matrix. The latter has been criticized to be often unreliable in the presence of a large number of assets (Shanken, 1992) and cannot be calculated when the panel is unbalance. However, panels of individual stocks are often unbalanced since stocks can be listed and delisted and firms can merge. Third, investors can more

[4] The problem must be solved numerically in the case weight constraints are added (i.e. weights must not become negative).

easily specify the desired level of risk, return and ESG for their portfolio, without having to set more abstract preference parameters. Fourth, the proposed model is flexible enough to accommodate different return-generating models from the simplest single-factor model to multi-factors models such as the Fama and French three-factor model (Fama and French, 1993). Moreover, the ESG dimension can be included as a simple characteristic that affects stock returns only or it can be considered as a risk factor that affects stock returns by means of changing their risk.

On the other side, we have to recall that equality constraints are more stringent that inequality ones and, at least in principle, may penalise the optimization result. For instance, portfolio risk might be penalised because the desired level of portfolio ESG score must perfectly meet a certain value, whereas in the case of a constraint according to which the ESG score of the portfolio must be equal to or greater than a specific quantity there might be more flexibility that can potentially lead to a more beneficial optimization result.

4. Dataset and descriptive statistics

We focus on single assets because the model by Varmaz et al. (2022) is suitable also for unbalanced panels so that we do not have to assume investment in funds as most of the literature on socially responsible portfolios rely on (Gasser, 2017). We adopt the optimization model starting from all the stocks that were part of the EURO STOXX Index, a subset of the STOXX Europe 600 Index, from January 2007 to August 2022. The selected index is very liquid and is frequently used as un underlying of both ETFs and derivatives. All the index components belong to large, mid and small capitalisation companies of 11 Eurozone countries therefore stock prices are expressed in the same currency (Euro) and are not affected by exchange rates.[5] The number of components in a given month is not fixed, but it is on average around 300 components every month. The final sample consists of 586 stocks and their monthly total returns, which include also dividends beside capital gains, are retrieved from Bloomberg.

We assume that stock returns are determined by a single-index model, as the one represented in equation (9), in which the only risk factor is the market factor and the ESG characteristic affects stock returns without modifying risk. In order to obtain the optimal weights solution in equation (14) we do not need to estimate the excess return of the market portfolio ($R_{m,t}$) and the reward for the ESG characteristic (c), because only the market beta (β_i) and the ESG score (θ_i) are required. Market betas are retrieved from Bloomberg and they are determined by comparing the price movements of the stock and the representative market for the past two years of weekly data; for example, for the

[5] The 11 countries are: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

Italian energy company Terna beta is calculated with respect to the FTSE MIB Index that is the primary benchmark index for the Italian equity market.

Stocks ESG characteristic is represented by the Bloomberg ESG disclosure score that is available on the Bloomberg terminal and measures the amount of ESG data a company discloses based on public data (sustainability reports, annual reports, websites, publicly available resources and direct contact with the companies being assessed). The choice is determined by two main reasons: first, Bloomberg ESG scores are available also for years further back with respect to other scores (e.g. Sustainalytics); second, this is novel with respect to previous studies, which mainly focus on scores provided by other agencies (e.g. Sustainalytics, Thomson Reuters, Refinitiv). [6] Moreover, we assume that a higher ESG commitment is associated to a higher transparency in the disclosure of socially responsible information and it may have a positive outcome on corporate social responsibility as maintained by some literature (Chen and Xie, 2022). Such scores range between 0 when none of the ESG data are disclosed and 100 when companies disclose every data point investigated. Bloomberg provides both individual scores on the three ESG pillars (environmental, social and governance) and an overall ESG score that equally weights the three individual scores.[7] In the present paper we focus on the aggregate measure of ESG, instead of single pillars, as the majority of studies on the optimization of sustainable portfolios (Varmaz et al. 2022; Gasser et al., 2017; Cesarone et al., 2022; Pedersen et al., 2021). However, given the demonstrated low correlation between ESG scores provided by different agencies we are aware that studies adopting different data providers are not fully comparable (Berg et al., 2019; Dimson et al., 2020; Gibson et al., 2021).

Table 1 presents some descriptive statistics of key variables to solve the optimization problem: market betas and ESG scores. The average stock sensitivity (β) to the market portfolio is 0.964 suggesting that our sample is on average well represented by the reference market, but minimum and maximum betas are -0.997 and 2.558 respectively. Low and negative values for beta are mainly referred to stocks that have been listed towards the end of the analysed period, so they show little or negative co-movement with the reference market; while betas higher than 2 are often associated to aggressive stocks that have been delisted during the analysed time period. The average ESG score is 34.019 with great variability across stocks; the minimum value is 0, indicating that Bloomberg does not assign any score, while the maximum average score in the sample is 70. When analysing the correlation between market beta the ESG score associated to each stock, it is on average very low (0.043) indicating that on average there are not dependencies between the two variables.

[6] Sustainalytics, for example, has a low coverage before 2014 and this is explained by the fact that before 2014, it was the needs of Sustainalytics clients that determined which companies received the ESG score (Auer, 2016).

[7] It has to be noted that the methodology for Bloomberg ESG Disclosure Scores was updated in early 2022, to account for the evolution of corporate ESG data reporting since the scores were originally created.

Table 1. Descriptive statistics of market betas and ESG scores

	Min.	**Median**	**Mean**	**Max**	**St. Dev.**	**P(25)**	**P(75)**
Mean β	-0.997	0.919	0.964	2.558	0.448	0.672	1.231
Mean ESG score (θ)	0.000	36.565	34.019	70.770	16.825	23.651	47.154
Corr (β, θ)	-0.860	0.048	0.043	0.897	0.381	-0.257	0.317

Notes: the table reports minimum, median, mean, maximum, standard deviation, 25^{th} percentile and 75^{th} percentile of the time series mean of market beta and ESG score. Corr (β, θ) indicates, for each of the 541 stocks Bloomberg assigns a score, the correlation between the time series of the score itself and the beta.

The number of stocks for which Bloomberg provides an ESG rating increases over time as shown in Table 2. In fact, in the first sub-period, from January 2007 to December 2010 the portfolio with non-rated stocks is the most diversified with an average number of stocks equal to 163, but the average number of components decreases up to 5 in the last sub-period. At the same time, ESG scores have, on average, an increasing trend as the disclosure of each company has grown over time. The latter is demonstrated by the fact that the 60-100 portfolio contains no assets up to 2010 while it represents the second most-populated portfolio in the period from January 2019 to August 2022.[8] The first and last sub-periods (Panel A and D of Table 2) are characterized by periods of crisis such as the global recession of 2008 and the Covid-19 pandemic in 2020, in fact they present some negative returns and a higher standard deviation with respect to the two sub-periods of normal market conditions (Panel B and C of Table 2). In each sub-period the return-risk reward (Mean/St. Dev.) tends to decrease as the values of the ESG score increases up to 50, then it slightly increases again. This trend is more evident in periods of normal market conditions, whereas it is less pronounced in sub-periods affected by crisis. However, we have to remember that portfolios with a score greater than 50 in 2007-2010 and portfolios with a score lower than 20 in 2019-2022 are scarcely informative since they contain few stocks.

[8] Similarly, the 50-60 portfolio has on average 22 stocks from January 2007 to December 2010 (but this number decreases to 10 if we consider the period January 2007 – December 2009), while it is the most diversified portfolio as of January 2019.

Table 2. Descriptive statistics of stock monthly returns for different ESG scores

Panel A: January 2007 – December 2010

ESG score	Median (%)	Mean (%)	St. Dev. (%)	P(25) (%)	P(75) (%)	Mean/St. Dev.	N
Not available	0.704	0.643	7.120	-2.168	4.284	0.090	163
0 - 20	0.614	-0.139	6.973	-3.100	4.485	-0.020	53
20 - 30	-0.794	0.090	7.297	-3.591	4.666	0.012	82
30 - 40	0.394	0.329	7.571	-3.397	5.214	0.044	78
40 - 50	-0.172	0.253	7.015	-3.231	4.962	0.036	62
50 - 60	0.514	0.789	5.623	-2.980	4.825	0.140	22
60 - 100	7.239	4.074	9.961	-3.879	12.467	0.409	0

Panel B: January 2011– December 2014

ESG score	Median (%)	Mean (%)	St. Dev. (%)	P(25) (%)	P(75) (%)	Mean/St. Dev.	N
Not available	1.143	1.371	4.759	-1.438	4.240	0.288	43
0 - 20	0.952	0.945	4.196	-1.075	3.615	0.225	53
20 - 30	0.911	0.663	4.370	-1.314	4.025	0.152	80
30 - 40	1.356	0.639	4.561	-2.201	3.896	0.140	80
40 - 50	0.274	0.634	4.953	-2.033	4.819	0.128	106
50 - 60	1.329	0.931	4.633	-0.973	3.917	0.201	80
60 - 100	1.230	0.498	5.035	-2.779	3.937	0.099	10

Panel C: January 2015 – December 2018

ESG score	Median (%)	Mean (%)	St. Dev. (%)	P(25) (%)	P(75) (%)	Mean/St. Dev.	N
Not available	2.300	1.757	5.175	-1.229	5.232	0.340	26
0 - 20	1.504	1.198	4.593	-2.064	4.856	0.261	21
20 - 30	1.421	0.886	4.431	-1.697	4.127	0.200	46
30 - 40	0.529	0.418	4.147	-1.957	3.233	0.101	61
40 - 50	0.464	0.228	4.259	-2.075	3.010	0.054	113
50 - 60	0.615	0.539	4.200	-1.796	3.273	0.128	136
60 - 100	0.885	0.644	4.491	-2.273	3.611	0.143	58

Panel D: January 2019 – August 2022

ESG score	Median (%)	Mean (%)	St. Dev. (%)	P(25) (%)	P(75) (%)	Mean/St. Dev.	N
Not available	0.798	-1.106	8.323	-7.535	4.856	-0.133	5
0 - 20	0.750	-0.404	9.749	-6.538	5.971	-0.041	4
20 - 30	2.901	1.403	6.537	-3.146	5.261	0.215	15
30 - 40	0.829	0.543	5.510	-2.814	3.439	0.098	40
40 - 50	1.840	0.602	6.420	-1.992	3.584	0.094	100
50 - 60	1.405	0.750	6.469	-1.818	3.927	0.116	163
60 - 100	1.508	0.760	6.171	-2.005	3.530	0.123	113

Notes: for each subsample the table reports return statistics (median, mean, standard deviation, 25th percentile, 75th percentile and the ratio between mean and standard deviation) of equally weighted portfolios that are made up of stocks with an ESG score indicated in the first column. “Not available” indicates the portfolio consisting of stocks for which Bloomberg does not assign a score, while, for example, the 0-20 portfolio consists of all the stocks with an ESG score greater that zero and lower than or equal to 20. The composition of such portfolios can change over time because ESG scores are not constant over time. Hence, we calculate the return in month t for each portfolio and we calculate those statistics on the time series of monthly portfolio returns. “N” in the last column indicates the time series average number of assets in each portfolio. In Panel A it is equal to zero for the 60-100 portfolio because that portfolio does not contain any stock up to January 2010 when it is made up of 1 stock, so the time series average is 0.25 that is approximated to 0.

5. Empirical methodology

In the empirical analysis we implement model (12) using the dataset described in Section 4 in order to obtain the optimal composition of portfolios characterized by specific levels of systemic risk (market risk) and ESG score. We set different values for the linear equality constraints concerning systemic risk and ESG, which are meant to represent possible strategies desired by investors. Specifically, beta can assume three values: 0.5 that is chosen by investors who desire a defensive portfolio, 1 chosen by investors desiring a portfolio that replicates the market and 1.5 that corresponds to the preference for an aggressive portfolio. As for the ESG score, we identify preferences for increasing levels of average portfolio ESG score (20, 30, 40, 50, 60) that correspond to an increasing attention towards sustainable investments. A target of 20 indicates a portfolio that is weakly sustainable while a target of 60 imposes a greater commitment in terms of sustainable assets. Therefore, we will obtain 15 portfolios given by combinations of desired levels of beta and ESG.

The third equality constraint, beside systemic risk and ESG, regards the budget constraint according to which the sum of optimal portfolio weights must be equal to 1, i.e investors cannot invest (if $\sum_{i=1}^{n} w_i < 1$) or borrow (if $\sum_{i=1}^{n} w_i > 1$) the additional funds at the risk-free rate. However, we allow for investors also going short on some assets, and optimal portfolios can be characterized by both long and short positions in the assets. This strategy can improve investors’ trade-off between risk and return and by shorting ESG assets with a lower ESG score they can obtain a better overall portfolio score (Pedersen et al., 2021; Fitzgibbons et al., 2018). On the other hand, by setting short sale constraints, investors avoid to have extreme long and short positions designed to exploit small differences in the structure of returns (Jacobs et al., 2014).

Once optimal weights are calculated according to equation (14), we compute out-of-sample realized returns with equation (15) for each period t and to do so we use beta and ESG score referred to period $t-1$. We have to recall that, differently from betas that are available monthly, Bloomberg provides ESG scores on an annual basis and are referred to a fiscal year, so in an out-of-sample perspective, the ESG score on December, 31 2006 impacts portfolio construction for the full fiscal year 2007. Then, starting from realized portfolio returns we measure portfolio performance over the whole period (2007-2022) by means of the Sharpe ratio, since it is a widely used measure appropriate also for returns that deviate from a normal distribution (Auer, 2016).[9] The Sharpe ratio for portfolio p is calculated as the ratio between the portfolio mean excess return μ and its standard deviation σ:[10]

$$SR_p = \frac{\mu}{\sigma} \tag{16}$$

Our final aim is to investigate the relation between portfolio Sharpe ratio and the desired level for portfolio systemic risk and ESG score.

In order to evaluate comparatively the model implemented on an unscreened sample, we also evaluate the performance of the optimal portfolio changes when the optimization is applied to a screened sample (resulting from negative screening), as is often the case in practice. To this end, we propose a first step in which we implement negative screening, i.e. we gradually exclude stocks that have a score lower than 20, 30, 40, 50. In the second step we apply two different types of optimization over the survived stocks: an optimization such as (12) and an optimisation that contemplates the minimization of residual risk assuming that asset returns are described by a traditional CAPM model. The second type of optimization, as represented by (17), does not assume that ESG scores can influence stock returns, as they are uniquely driven by systemic risk, anyway the use of a screening strategy excludes less virtuous stocks that a sustainable investor might want to exclude from the portfolio. In fact, the model does not impose a binding equality constraint with respect to the portfolio average ESG score, but lets it to be determined by the model and conditioned by the screening. The corresponding optimization model is represented below:

$$\begin{aligned} \min_{w} \quad & \frac{1}{2} w^T w \\ \text{s.t.} \quad & w^T 1 = 1 \\ & w^T \beta = \beta_P^* \end{aligned} \tag{17}$$

6. Results

In this Section we present the results from the Varmaz et al. (2022) portfolio optimization model that incorporates the ESG dimension as represented by (11). In Section 6.1. we investigate the relation between portfolio performance, measured by the Sharpe ratio, and portfolio desired level of ESG score; whereas in Section 6.2. we analyse the performance of the optimization model when it is applied to a screened sample. In this latter case we consider both an optimization model that, among

[9] Studies by Schuhmacher and Eling (2011 and 2012) demonstrate that the conditions for the decision-theoretic foundation of the Sharpe ratio are the same of other admissible performance measures that are skewed and exhibit fat tails i.e. are more realistic. Further, also the resulting performance ranking is the same.

[10] The risk-free rate chosen to compute excess returns is the 1-month Euribor retrieved from the database of the German Central Bank (https://www.bundesbank.de/en/statistics/time-series-databases).

others, imposes a constraint on the average portfolio ESG score as represented by (12), and an optimization model that does not set any constraints on the ESG dimension as in (17).

6.1. Desired portfolio ESG score and portfolio performance

By means of equation (14) we determine, for each month of the dataset, the optimal weights of 15 portfolios characterized by different desired levels of portfolio beta (0.5, 1, 1.5) and portfolio ESG score (20, 30, 40, 50, 60) and we calculate the out-of-sample realized return in the next month.[11] Then, for each portfolio we obtain a time series of realized returns that we use to calculate portfolio performance by means of the Sharpe ratios, which are reported in Table 3. A few results over the whole period 2007-2022 clearly emerge.

First, for each level of systemic risk, the Sharpe ratio of the optimal portfolio is negatively and monotonically related to the target ESG level. In fact, when beta is equal to 1, the Sharpe ratio of the portfolio with an average score of 20 is 0.012; the latter decreases to 0.006 when portfolio score is 30 and becomes negative when the ESG score is 50 or higher. The same monotonicity is true for defensive portfolios (with beta equal to 0.5) and for aggressive portfolios (with beta equals to 1.5). Second, when keeping the ESG score constant, we observe a negative relationship between systemic risk and performance, with the only exception of portfolios with ESG score equal to 60 for which the performance slightly improves from -0.015 (portfolios #5 and #10) to -0.014 (portfolio #15). This result suggests that portfolio total risk (that corresponds to the denominator of the Sharpe ratio) increases more than systemic risk whereas, according to the single-factor model, portfolio return compensates systemic risk only.

Comparison with Varmaz et al. (2022) highlight a main difference, since they find that the optimal portfolio performance increases along with the desired ESG score. This different result can be explained by the different structure of their dataset (stocks from the US S&P 500 Index and ESG scores from Refinitiv Datastream) whose descriptive statistics show that stocks with higher ESG score benefit also of a higher performance. In our analysis, even if the return-risk ratio associated to portfolios with an ESG score greater that 50 slightly increases with respect to portfolios with an ESG score between 30 and 50 (Table 2), we do not observe such improvement in optimal portfolio performance (Table 3). This might be due to the model that must satisfy an equality constraint on ESG score, hence investors must take greater short positions on low (or no) rated stocks which, however, are characterised by a higher risk-return ratio. Furthermore, since optimal portfolios are characterized by a long or short position in almost every asset, the inclusion of a very high ESG equality constraint gives the model little flexibility, which may result in a worse performance.

[11] Constraints on the level of beta and ESG must be satisfied in each month.

Table 3. Optimal portfolio performance for different levels of beta and ESG score

Whole period 2007-2022

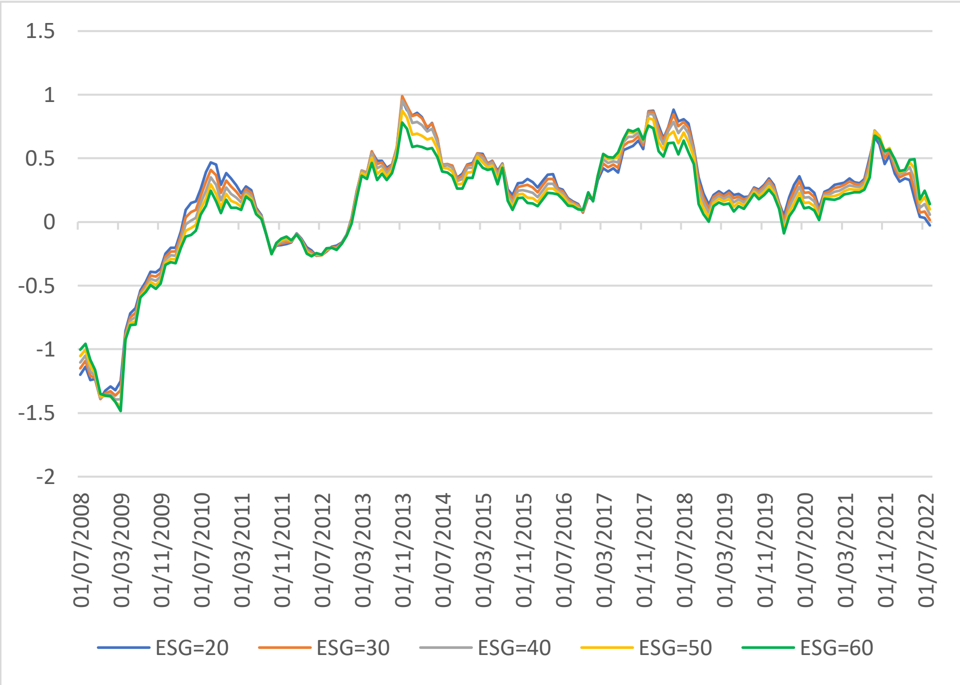
#P	β	ESG score (θ)	Mean	St.Dev.	SR
1	0.5	20	0.089	4.928	0.018
2	0.5	30	0.048	4.853	0.010
3	0.5	40	0.008	4.835	0.002
4	0.5	50	-0.033	4.874	-0.007
5	0.5	60	-0.074	4.969	-0.015
6	1	20	0.074	5.971	0.012
7	1	30	0.033	5.905	0.006
8	1	40	-0.008	5.885	-0.001
9	1	50	-0.049	5.913	-0.008
10	1	60	-0.090	5.987	-0.015
11	1.5	20	0.058	7.271	0.008
12	1.5	30	0.017	7.213	0.002
13	1.5	40	-0.024	7.194	-0.003
14	1.5	50	-0.064	7.213	-0.009
15	1.5	60	-0.105	7.269	-0.014

Notes: #P indicates the progressive number of portfolios; β the average desired exposure to systemic risk and θ the desired ESG score of the portfolio. Each combination of β and θ identifies an investor-specific portfolio. Mean, standard deviation and SR (Sharpe ratio) refer to the time series of out-of-sample portfolio realized returns. In each portfolio the budget constraint is respected, so the sum of portfolio weights is 1.

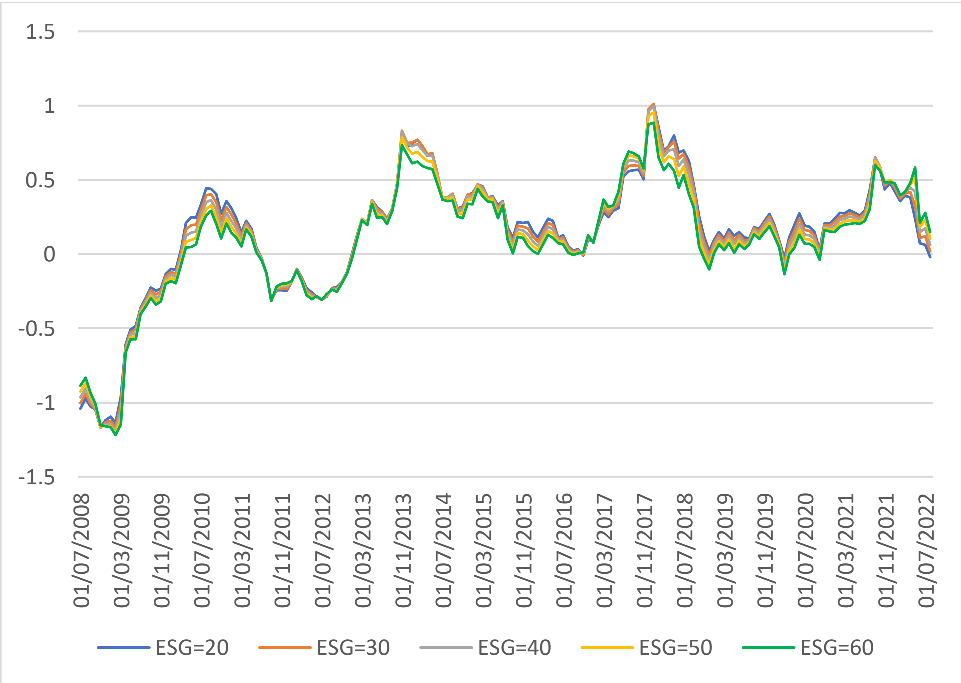
In order to investigate whether results change when focusing on shorter subperiods, we compute a rolling Sharpe ratio, with windows width equal to 18 months. Rolling Sharpe ratios are represented graphically in Figure 1. Each panel of the figure (a-c) refers to different levels of systemic risk. Since they do not show relevant differences, for reasons of space we focus on the case in which beta is equal to 0.5. The green and yellow lines, representing portfolio with an ESG score of 60 and 50 respectively, underperform the other portfolios most of the time. Focusing on the period following December 2010, in which there are few stocks with a high ESG score, the Sharpe ratios of portfolios with high ESG score (50 and 60) seem to depend on market phases. In fact, they are very close to/higher than the Sharpe ratio of other portfolios in periods of bull market such as 2012-2013 and 2017 (when Sharpe ratio of all portfolios is increasing), whereas they underperform in periods of constant/bear market such as from 2013 to 2016 (when Sharpe ratio of all portfolios is almost constant or decreasing). Finally, in the last period after 2020, when stocks with a high ESG represent most of the sample, high-ESG portfolios overperform even if the general Sharpe ratio of the market is declining.

Figure 1. Portfolios' rolling Sharpe ratio for different levels of ESG score

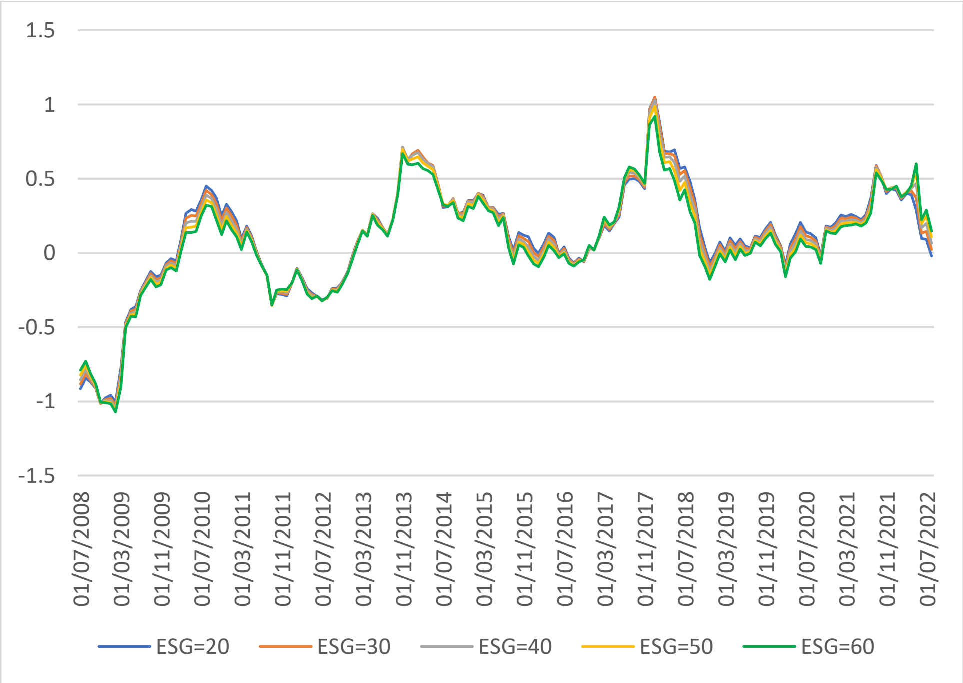
a) β = 0.5



b) β = 1



c) $\boldsymbol{\beta}$ **= 1.5**



Notes: each subfigure represents the Sharpe ratio at the same beta level and for different ESG score levels. Rolling window width = 18 months.

6.2. Portfolio optimization over a screened sample

The second part of the empirical analysis presents a comparison between two main strategies to set up optimal sustainable portfolios, i.e. the model analysed in Section 6.1., whereby optimization is performed over an unscreened sample, and models that optimize over a negatively screened sample.

First of all, we apply negative screening strategies consisting, each month, in the exclusion of stocks that have an ESG score lower than a certain threshold and then we use model (12) in order to obtain an optimal portfolio over a screened sample. Note that the resulting optimal portfolio also satisfies the constraint regarding a desired average ESG score. Optimal portfolio performances are reported in Table 4 and each portfolio can be compared with the corresponding portfolio (#P) of Table 3, since they are characterized by the same level of systemic risk and average ESG score. For defensive portfolios (with beta equal to 0.5) it results that, by screening the investment set, investors obtain a lower performance. Hence, the exclusion of stocks with the weakest ESG score, causes the portfolio to suffer from a limited diversification. The same is true for portfolios with a higher beta, except when we impose a very high exclusion threshold (e.g. 50). This might be due to the fact that, in our sample, stocks with a score greater than 50 are also associated to a relatively high return-risk reward (Table 2).

Our results are almost in line with Pedersen et al. (2021) who show that the ESG-Sharpe ratio frontier resulting from a screened sample lies below the one resulting from an unconstrained sample, however they adopt screening strategies slightly different from ours consisting in removing the worst 10% and 20% of the weakest ESG stocks.

Table 4. Optimal portfolio performance (considering ESG) over a screened sample

#P	Screening	β	ESG score (θ)	Mean	St.Dev.	SR
1	≥ 20	0.5	20	-0.124	5.056	-0.024
2	≥ 30	0.5	30	-0.211	4.975	-0.042
3	≥ 40	0.5	40	-0.223	4.954	-0.045
4	≥ 50	0.5	50	-0.086	5.252	-0.016
5	≥ 60	0.5	60	-	-	-
6	≥ 20	1	20	-0.145	6.250	-0.023
7	≥ 30	1	30	-0.214	6.285	-0.034
8	≥ 40	1	40	-0.180	6.209	-0.029
9	≥ 50	1	50	0.139	6.068	0.023
10	≥ 60	1	60	-	-	-
11	≥ 20	1.5	20	-0.167	7.708	-0.022
12	≥ 30	1.5	30	-0.217	7.876	-0.028
13	≥ 40	1.5	40	-0.137	7.795	-0.018
14	≥ 50	1.5	50	0.365	7.635	0.048
15	≥ 60	1.5	60	-	-	-

Notes: #P indicates the progressive number of portfolios and screening ≥ a certain threshold indicates that we exclude all stocks with an ESG score lower than the threshold from the portfolio optimization. β indicates the average desired exposure to systemic risk and θ the desired ESG score of the portfolio. Each combination of screening, β and θ identifies an investor-specific portfolio. Mean, standard deviation and SR (Sharpe ratio) refer to the time series of out-of-sample portfolio realized returns. In each portfolio the budget constraint is respected, so the sum of portfolio weights is 1. Portfolios #5, #10 and #15 are empty because in some months there are no stocks satisfying the screening.

Then, we combine negative screening strategies with model (17). In this case we allow for more flexibility about the average ESG score of the portfolio since we do not impose any constraints on it. In fact, the optimal portfolio performance (Table 5) has a better performance w.r.t. the previous case (Table 4). Also in this case portfolios resulting from a heavy screening perform better than the original Varmaz et al. (2022) model over an unscreened sample.

Table 5. Optimal portfolio performance (non-considering ESG) over a screened sample

#P	Screening	β	Mean	St.Dev.	SR
1	≥ 20	0.5	-0.013	4.772	-0.003
2	≥ 30	0.5	-0.024	4.686	-0.005
3	≥ 40	0.5	-0.037	4.660	-0.008
4	≥ 50	0.5	0.041	4.537	0.009
5	≥ 60	0.5	-	-	-
6	≥ 20	1	-0.032	5.951	-0.005
7	≥ 30	1	-0.025	5.928	-0.004
8	≥ 40	1	-0.006	5.877	-0.001
9	≥ 50	1	0.200	5.643	0.036
10	≥ 60	1	-	-	-
11	≥ 20	1.5	-0.050	7.410	-0.007
12	≥ 30	1.5	-0.025	7.496	-0.003
13	≥ 40	1.5	0.025	7.457	0.003
14	≥ 50	1.5	0.360	7.386	0.049
15	≥ 60	1.5	-	-	-

Notes: #P indicates the progressive number of portfolios and screening ≥ a certain threshold indicates that we exclude all stocks with an ESG score lower than the threshold from the portfolio optimization. β indicates the average desired exposure to systemic risk. Each combination of screening and θ identifies an investor-specific portfolio. Mean, standard deviation and SR (Sharpe ratio) refer to the time series of out-of-sample portfolio realized returns. In each portfolio the budget constraint is respected, so the sum of portfolio weights is 1. Portfolios #5, #10 and #15 are empty because in some months there are no stocks satisfying the screening.

7. Conclusions

This paper is motivated by the relevance for the financial industry of introducing the ESG dimensions in setting up optimal portfolios and it has two main objectives. First, to make the state of art on the theoretical and empirical literature focusing on the set up ESG compliant portfolios. Second, given the absence of consensus in empirical literature and the limited number of studies providing performance comparison of ESG strategies, we propose an original contribution on the impact of ESG considerations on optimal portfolios and on the comparison of different approaches to set up an ESG compliant portfolio. In the comparison we account on the one hand for screening strategies, which are more transparent on the exclusion policy but impose a severe reduction in the investment universe and portfolio diversification, on the other, for constrained optimizations in consideration of ESG, which do not imply a screening on the investment universe but are less transparent on the asset selection policy.

In our original contribution, we follow the approach by Varmaz et al. (2022) over both an unscreened and a screened sample starting from the 586 stocks that composed the EURO STOXX Index over the period January 2007 – August 2022. Varmaz et al. (2022) is an innovative optimization model that minimizes portfolio residual risk by imposing a desired level of portfolio average systemic risk and ESG (measured here by Bloomberg ESG score). In doing so we provide answers to two main research questions: Are optimal portfolios with a high ESG score penalized by a lower financial performance? Does portfolio performance deteriorate when we focus on a negatively screened sample instead of an unscreened one?

Three are the main results. First, regardless of the level of portfolio systemic risk, the Sharpe ratio of the optimal portfolios worsens as the target ESG level increases. Second, the Sharpe ratio of portfolios with the highest average ESG scores (i.e. 50 and 60) shows a dynamics that follows market phases: it is very close to/higher than the Sharpe ratio of other portfolios in periods of bull market, whereas underperforms in periods of constant or bear market suggesting that ESG portfolios do not seem to represent a safe haven. Third, when we adopt a negative screening with medium-low threshold, the optimization model suffers of a general reduction in the performance with respect to on optimization over an unscreened sample. However, we obtain a superior performance when adopting a very severe screening implying that focusing on very virtuous companies allows investors to do well by doing good.

In sum, the innovative model by Varmaz et al. (2022) is characterized by several advantages. It provides results that are strongly related to the dataset structure and is able to represent the relation between asset returns and ESG scores quite accurately. In fact, in the original contribution by Varmaz et al. (2022), the model shows an increasing performance as the overall ESG score of the optimal portfolio increases, consistently with descriptive statistics highlighting that stocks with higher ESG score benefit also of a higher performance. These results are different from ours because are based on a different sample consisting of stocks from the US S&P 500 Index and ESG scores from Refinitiv Datastream. Moreover, such a model reduces the computational complexity of the problem and is suitable in the presence of unbalanced panels and investor-specific desired levels of both portfolio systemic risk and sustainability. Hence, this new approach is extremely relevant for the asset management industry as it introduces assets with shorter time series in optimized portfolios and simplifies the selection of the optimal portfolio that meets investors' preferences, also in line with the revision of the European Union's MiFID II directive.

Further developments could regard the comparison between our dataset and the one used in Varmaz et al. (2022) empirical application. Such comparison can be conducted in two directions. First, we could investigate how the relation between ESG and single stocks risk-return compensation changes in sub-periods (such as after 2020) in which we find that performance increases as optimal portfolios becomes more sustainable. Second, we could repeat the analysis by using the ESG rating provided by a different agency such as Refinitiv Datastream, which also allows us to shed light on the debate about the divergence of ESG rating agencies.

A final development could consist in introducing more risk factors (i.e. Fama and French size and value factors) beside an ESG risk factor in our model, to test whether the performance of optimal portfolios changes when a different return generating process is assumed.

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