

Sustainable optimal portfolios:

Optimizing after screening vs. constraining optimization (or the best of both)?*

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Abstract

The aim of this paper is to compare two philosophically different strategies to obtain (Environmental, Social, Governance) ESG-compliant portfolios and to propose a third one. We confront the risk-adjusted performance of three optimal portfolios: the first results from optimization on an ESG-screened sample, the second is obtained by including a portfolio ESG-score constraint in the optimization on an unscreened sample, the third results from our proposal of taking pros of both by optimizing with an ESG constraint (so as to reach a target) over a slightly screened sample (so as to eliminate companies with lowest sustainability). The optimization approach rests on minimizing portfolio residual risk, it does not require a balanced dataset and it is implemented with Bloomberg ESG scores over a stock sample from the EURO STOXX Index in the period January 2007 – August 2022. Two are the main results. First, the performance of an ESG-compliant portfolio depends not only on the strategy taken (optimizing after screening, constraining optimization, mixed strategy) but also on the feature of the initial investment set in terms of relationship between ESG scores and the risk-reward (monotone, convex, concave). Second, the comparative performance of the three strategies over time does not change much with the financial cycle. The most interesting implication is that, the third strategy we propose, allows sustainable investors to do well by doing good in the presence of both a convex and a monotone investment set, being thus able to attract a larger pool of investors towards ESG-compliant optimal portfolios.

Keywords: Finance, sustainable portfolio, portfolio optimization, ESG score, 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. Crises played an important role in raising investors' awareness towards social responsibility and sustainability issues: the 2007-2008 global financial crisis highlighted the importance of corporate social responsibility (Cesarone et al., 2022), while Covid-19 pandemic transformed sustainability from a luxury good into a priority (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 ESG-compliant 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 to provide comparative evidence on the performance of two philosophically different strategies to set up an ESG-compliant portfolio and to propose a third one resulting from a mixture of them: the first, which is widely adopted in the industry, results from optimization on an ESG-screened sample, the second is obtained by adding to the optimization problem a portfolio ESG-score constraint on an unscreened sample, while the third results from our proposal of taking pros of both by optimizing with an ESG-score constraint (so as to reach a target) over a slightly screened sample (so as to eliminate only the worst companies in terms of ESG).

As far as we know this is the second study, after Varmaz et al. (2022), to implement the a priori approach as defined by Gasser et al. (2017) to solve the tri-criterion optimization model (risk-return-ESG) and the first one to implement such an approach over an EU sample. Moreover, in this study we also propose an application of this approach over a screened sample so we can compare our results with the most used portfolio screening strategies (e.g. Auer, 2016; Bertelli and Torricelli, 2022).

The choice to follow Varmaz et al. (2022), which determines the optimal portfolio by minimizing residual risk for a given level of systemic risk and ESG score, has technical and practical advantages: 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 the investment set also stocks with shorter time series.

Our dataset is based on 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 Bloomberg ESG disclosure score, which assesses firm’s transparency on ESG issues.

Two are the main results. First, the performance of an ESG-compliant portfolio depends both on the strategy taken (optimizing after screening, constraining optimization or both) and the feature of the initial investment set in terms of relationship between ESG scores and the risk-reward (monotone, convex, concave). In fact, prior screening implies a superior risk-adjusted performance only with heavy screening, an ESG-score constraint in optimization implies portfolio performance worsens as the target ESG level increases; optimizing with an ESG constraint after a mild ESG screening reverses the previous result. However, these results are driven by the convex relationship between ESG scores and the risk-reward relation of the initial dataset. Second, when testing for the ESG-compliant portfolio that better performs over time, we find that the comparative performance of the three strategies does not change much over the financial cycle. The most interesting implication for the financial industry and the real economy is that, the third strategy we propose, allows sustainable investors to do well by doing good in the presence of both a convex and a monotone investment set, being thus able to attract a larger pool of investors towards ESG-compliant optimal portfolios

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, Section 4 the dataset, and Section 5 the empirical methodology. Section 6 presents results on the risk-adjusted performance of three different types of ESG-compliant portfolios and Section 7 compares portfolio performance over the whole period and over time. Section 8 presents some robustness tests. 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 ratings useful to evaluate companies’ nonfinancial performance in consideration of ESG factors.

There are several strategies, characterized by different levels of complexity and sophistication to 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 various strategies can be essentially grouped into three main strands as 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 the involvement in immoral activities or low ESG measures, while positive screening tilts portfolio towards companies outperforming 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 ratings, screening is achieved by the exclusion (selection) of assets associated to low (high) scores. As far the portfolio composition, rather than resting on optimization, two main simple alternatives are followed: equal weights or weights resting on market capitalization.

Overall, the literature is inconclusive about the impact of ESG-related criteria on financial portfolio performance.¹ 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 consideration of the ESG dimension from the portfolio construction (Bender et al., 2017). According to this approach the first step is a screening based on ESG scores over the constituents of a diversified index, the second is the set up of an optimal portfolio problem with the survived assets. 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 based on some optimizing criterion (e.g. minimize portfolio risk or a 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: Simple Exclusion by cap-weighting the survived stocks and Optimized

¹ In the literature prior to the diffusion of ESG rating, the measurement was often made in terms of Corporate Social Responsibility (CSR) whereby ESG can be thought of a metric for CSR (Kuzey et al., 2021).

Exclusion by weighting the survived securities to minimize the tracking error with respect to the benchmark. The Optimized Exclusion portfolio 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, it has a higher extra-return with respect to the benchmark than the Simple Exclusion portfolio. Liagkouras et al. (2020) first perform a screening over the constituents of FTSE-100 index to exclude assets that do not respect an ESG constraint, then they solve a mean-variance portfolio optimization model. They find that the optimal allocation of assets with high ESG score is characterized by a worse risk-return combination than optimized portfolios of the unscreened sample concluding that ESG investors must be willing to pay for sustainability. 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 limit 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 an ESG target) to the portfolio mean and variance objectives (Hirschberger et al., 2013; Utz et al., 2014; Cesarone et al., 2022).²

Gasser et al. (2017) are the first to clearly argue that such a tri-criterion optimization model can be implemented either in an a posteriori or a priori fashion: the former identifies the set of efficient portfolios on an efficient surface (as opposed to the Markowitz efficient frontier) and, given investors' preference parameters, calculates the single optimal portfolio maximizing investors' utility; the latter consists in finding the optimal portfolio by solving the optimization problem for a given set of investors' preferences about risk, return and ESG.

The a posteriori approach, adopted by most of the existing literature, requires the construction of the efficient (or nondominated) surface. For instance, Gasser et al. (2017) examine the relations between return, risk and social responsibility in a tri-dimensional space on a set of international stocks and find that mean-variance-ESG efficient portfolios tend to obtain a lower Sharpe ratio than mean-variance efficient portfolios. Further, Utz et al. (2014) use the approach by Hirschberger et al. (2013) to compute the mean-variance-ESG nondominated surface that minimizes portfolio risk and maximizes portfolio expected return and ESG, and by means of an inverse optimization process they investigate whether US socially responsible mutual funds, that are based on negative screening, have a higher ESG risk tolerance than US conventional mutual funds in the period 2001-2010.³ Their findings suggest that the initial screening is not sufficient to increase the

² 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).

³ Given that existing mutual fund portfolios are likely to be inefficient, Utz et al. (2014) implement the inverse optimization process over the closest matched portfolios that are on the nondominated surface.

sustainability of the fund, since conventional and socially responsible mutual funds do not show significant differences in terms of ESG risk tolerance and ESG score. Similarly, Utz et al. (2015) and Alessandrini and Jondeau (2021) prove that screening the initial investment set does not always guarantee a higher ESG quality and a superior financial performance with respect to efficient portfolios aiming to maximize portfolio ESG score. The former use an algorithm transformation method (the ε -constrained method) to convert the unconstrained problem into a constrained one and compute efficient portfolios on the nondominated surface that maximize portfolio sustainability by imposing conditions of risk and expected return that are no worse than those of screened US mutual fund portfolios.⁴ The latter compare screened portfolios with optimal portfolios maximizing portfolio ESG score by imposing restrictions on the tracking error, transaction costs, and risk exposures over individual stocks from the MSCI ESG database in the period 2007-2018. The ε -constraint method is adopted also by Cesarone et al. (2022) in order to identify the risk-expected return-ESG relations embedded in the nondominated frontier. They minimize portfolio variance by imposing constraints on portfolio target return and target ESG for five different datasets representing indexes from major stock markets (Dow Jones Industrial, Euro Stoxx 50, FTSE100, NASDAQ100, S&P500) from 2006 to 2020. By varying such target levels they obtain efficient portfolios (i.e. on the efficient surface) and find that, over the full period 2006-2020, 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. Finally, another a posteriori application is proposed by Pedersen et al. (2021) who synthesize risk and return with the Sharpe ratio deriving a nondominated frontier, instead of a surface and thus restate the optimization problem across three dimensions (risk, return, ESG) in terms of a trade-off between ESG and Sharpe ratio. However, Steuer and Utz (2023) argue that combining risk and return objectives into a Sharpe ratio objective turns the problem into a bi-criterion one and this may lead to a non-optimal solution in terms of risk and return.

The a priori approach to solve the mean-variance-ESG optimization problem was first presented by Gasser et al. (2017) who illustrated the theoretical model without providing an empirical implementation. Only recently, Varmaz et al. (2022) reformulates the a priori approach by assuming the validity of a factor model for asset returns, thus overcoming some model-specific issues (i.e. the estimation of the covariance matrix and the identification of investors' return, risk and ESG preference parameters) and obtaining an analytical solution: the single optimal portfolio that minimizes residual risk and is consistent with investors' desired levels of systemic risk and sustainability. Moreover, the reformulation proposed by Varmaz et al. (2022) is flexible to accommodate the two competing interpretations of the ESG dimensions: ESG features have an effect on portfolio return because they modify portfolio exposure to systemic risks (e.g. Pedersen et al., 2021; Pástor et al., 2021) vs. ESG scores contribute to an additional expected return that is unrelated to

⁴ The ε -constraint method is a technique used to solve multicriteria optimization problems. It reformulates the original problem by optimizing only one of the original objectives while the others enter the optimization problem as constraints (Haimes et al., 1971) and uses the ε level comparison, which compares search points based on the pair of objective value and constraint violation of them.

assets' systemic risk (e.g. Bénabou and Tirole, 2010; Edmans, 2011; Friede et al., 2015; Hoepner et al., 2021).

In sum, against the recent flourishing of optimization models considering the ESG dimension, most studies solve the tri-criterion optimization through an a posteriori approach mainly focusing on the mean-variance-ESG surface rather than finding the optimal portfolio consistent with investors' preferences, and only few studies compare the financial performance of optimal portfolios resulting from different strategies (e.g. tri-criterion optimization vs. strategies that apply screenings before the optimization process). To be noted that optimization models based on an efficient mean-variance-ESG surface need balanced panels to be implemented, which restricts implementation to mutual funds, market indexes or stocks with long time series.

3. The analytics of the optimization model

All the strategies we compare in this paper produce an optimal portfolio and thus require an optimization framework. To this end, among alternatives described in Section 2.3, we follow the a priori approach reformulation by Varmaz et al. (2022) for three main reasons: it has a great usability by the industry since it allows to set a priori desired levels of portfolio systemic risk and ESG score without the need for investors' preference parameters, it provides an analytical solution without the need of estimating the variance-covariance matrix, and it is suitable also in the presence of unbalanced panels. The latter feature is particularly relevant when accounting for the ESG dimension over time since the investment set consists of assets with different time of listing, implying the dataset is an unbalanced panel.

In this Section we describe the optimization model that we use starting from a traditional mean-variance optimization framework extended to include an ESG constraint (Section 3.1) to end up with the reformulation by Varmaz et al. (2022) that brings the above-cited technical advantages both in the presence and in the absence of an ESG constraint (Section 3.2).

3.1. Mean-variance optimization: the inclusion of an ESG objective

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:⁵

$$\begin{aligned} \max_w \quad & \alpha\mu_P - \frac{1}{2}\lambda\sigma_P^2 \\ \text{s. t.} \quad & w^T \mathbf{1} = 1 \end{aligned} \tag{1}$$

where:

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

$\alpha =$ scalar that represents investor's return preference;

⁵ 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.

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

λ = 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.

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 ESG scores across assets in line with Drut (2010). It results in the following tri-objective optimization problem:

$$\begin{aligned} \max_w \quad & \alpha \mu_P - \frac{1}{2} \lambda \sigma_P^2 + \epsilon \theta_P \\ \text{s. t.} \quad & w^T \mathbf{1} = 1 \end{aligned} \quad (2)$$

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 Lagrangian function:

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

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

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

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:

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

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:⁶

$$\begin{aligned} \min_w \quad & \frac{1}{2} w^T V w \\ \text{s. t.} \quad & w^T \mathbf{1} = 1 \\ & w^T \mu = \mu_p^* \\ & w^T \theta = \theta_p^* \end{aligned} \quad (6)$$

The resulting optimal portfolio is a minimum variance portfolio on the efficient set 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:

$$\min_w \Lambda: \quad \frac{1}{2} w^T V w - x(w^T \mathbf{1} - 1) - y(w^T \mu - \mu_p^*) - z(w^T \theta - \theta_p^*) \quad (7)$$

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

$$w = xV^{-1}\mathbf{1} + yV^{-1}\mu + zV^{-1}\theta \quad (8)$$

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 reformulation by Varmaz et al. (2022): with and without ESG constraint

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.⁷ This vision is supported by both theoretical (Bénabou and Tirole, 2010) and empirical (Edmans, 2011; Friede et al., 2015) literature. Hence an 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):

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

⁶ 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 $\frac{1}{2}w^T V w$.

⁷ 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.

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 $\frac{cov(R_i, R_m)}{\sigma_{R_m}^2}$ with $\sigma_{R_m}^2$ 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):

$$\begin{aligned}\sigma_p^2 &= w^T V w \\ &= w^T (\beta \sigma_{R_m}^2 \beta^T + RV) w\end{aligned}\quad (10)$$

where:

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

β = $N \times 1$ vector of assets' sensitivities to the market factor

RV (residual variance) = diagonal $N \times N$ matrix of the unsystematic part of asset i variance (σ_{ε_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 constraint 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 substituted by the identity matrix without changing the result of the optimization problem that becomes as follows:

$$\begin{aligned}\min_w \quad & \frac{1}{2} w^T w \\ \text{s. t.} \quad & w^T \mathbf{1} = 1 \\ & w^T \beta = \beta_p^* \\ & w^T \theta = \theta_p^*\end{aligned}\quad (11)$$

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

$$\begin{aligned}\min_w \quad & \frac{1}{2} w^T w \\ \text{s. t.} \quad & X^T w = b\end{aligned}\quad (12)$$

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 Lagrangian multipliers:

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

The solution differs across investors, because they have individual preferences for the desired values in vector b , and is represented by equation (14):

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

Problem in (12) is reported without specifying the subscript t , but it can be solved for each time t 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

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

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.⁸ 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 unbalanced, whereby panels of individual stocks are often unbalanced since stocks can be listed and delisted and firms can merge. Third, investors can more 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-factor 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.

This reformulation is useful also when optimizing without an ESG constraint, over an ESG-screened sample. In fact, assuming that asset returns are described by a traditional CAPM model, hence driven by systemic risk only, the optimal portfolio can be found by minimizing residual risk as follows:

⁸ The problem must be solved numerically in the case weight constraints are added (i.e. weights must not become negative).

$$\begin{aligned}
\min_w \quad & \frac{1}{2} w^T w & (16) \\
\text{s. t.} \quad & w^T \mathbf{1} = 1 \\
& w^T \beta = \beta_p^*
\end{aligned}$$

However, we have to recall that equality constraints are more stringent than inequality ones and, at least in principle, may penalize the optimization result. For instance, portfolio risk might be penalized 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 can focus on single assets because the model in (11) is suitable also for unbalanced panels so that we do not have to assume investments in funds as most of the models in the literature (see Section 2.3). We start 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. All the index components belong to large, mid and small capitalization companies of 11 Eurozone countries therefore stock prices are expressed in the same currency (Euro) and are not affected by exchange rates.⁹ 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 the risk profile. 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 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.

The ESG dimension in stocks is quantified by the Bloomberg ESG disclosure score that 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 advantage of the Bloomberg ESG scores is that they are available for years further back with respect to other scores (e.g. Sustainalytics).¹⁰ Moreover, this metrics is supported by the literature whereby a higher ESG

⁹ The index is very liquid, in fact it is frequently used as an underlying of both ETFs and derivatives. The 11 countries are: Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain.

¹⁰ 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).

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 (Chen and Xie, 2022). These scores range between 0, if there is no ESG data disclosure, and 100 when companies disclose every relevant data points. 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.¹¹ In the present paper we focus on the aggregate measure of ESG to gauge overall sustainability and in line with most studies on optimal sustainable portfolios (Varmaz et al. 2022; Gasser et al., 2017; Cesarone et al., 2022; Pedersen 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 on average well represents the reference market, although with a wide range (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 thus showing little or negative co-movement with the market; while betas higher than 2 are mostly 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, i.e. no Bloomberg score, while the maximum average score is 70.770. The correlation between market beta the ESG score for each stock is on average very low (0.043) indicating that on average the two variables are quite independent.

Table 1. Descriptive statistics of market betas and ESG scores
Whole sample, whole period 2007-2022

| | 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, 25th percentile and 75th 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.

In Table 2 we report descriptive statistics focusing on different levels of ESG score (including the non-availability of the score itself) for the whole period and for two subperiods. Specifically, three different classes of ESG scores are defined (0-30, 30-50, 50-100) so as to have the same number of assets over the whole period, however the statistics obtained are robust to different ESG clustering (available upon request).

The statistics on different ESG-score classes gives more insight on the relation between ESG scores and the return-risk reward, while those on different subperiods provide information on the temporal distribution of ESG scores that has varied greatly over time. Descriptive statistics over the whole period

¹¹ 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.

(Panel A) and over subperiod (Panel B and C) show that the relation between return-risk reward (Mean/St. Dev.) and ESG score is substantially convex, being lower for intermediate ESG ratings (30-50) and higher for the lowest (0-30) and the highest rating (50-100) classes. By focusing on subperiods, the dynamic of the ESG market emerges. First, the number of stocks with a Bloomberg ESG score increases over time: the first subperiod (Panel B) from January 2007 to December 2014 represents an ESG market in its infancy, as demonstrated by the fact that most stocks (237) are in the first class with low (or no) scores, while the second subperiod (Panel C), from January 2015 to August 2022, refers to a more developed ESG market spurred, in 2015, by both the UN 2030 Agenda and the Paris Agreement on climate change and most stocks (233) are in the highest rating class (50-100).

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

Panel A: Whole period: January 2007 – August 2022

| ESG score | Median (%) | Mean (%) | St. Dev. (%) | P(25) (%) | P(75) (%) | Mean/St. Dev. | N |
|-----------|------------|----------|--------------|-----------|-----------|---------------|-----|
| 0 - 30 | 1.369 | 0.756 | 5.409 | -2.193 | 3.939 | 0.140 | 151 |
| 30 - 50 | 0.820 | 0.449 | 5.615 | -2.502 | 3.856 | 0.080 | 161 |
| 50 - 100 | 0.973 | 0.759 | 5.186 | -2.091 | 3.927 | 0.146 | 142 |

Panel B: First subperiod: January 2007– December 2014

| ESG score | Median (%) | Mean (%) | St. Dev. (%) | P(25) (%) | P(75) (%) | Mean/St. Dev. | N |
|-----------|------------|----------|--------------|-----------|-----------|---------------|-----|
| 0 - 30 | 1.349 | 0.569 | 5.761 | -2.171 | 4.063 | 0.099 | 237 |
| 30 - 50 | 0.735 | 0.471 | 6.095 | -2.668 | 4.736 | 0.077 | 163 |
| 50 - 100 | 0.865 | 0.846 | 5.125 | -2.431 | 4.395 | 0.165 | 56 |

Panel C: Second subperiod: January 2015 – August 2022

| ESG score | Median (%) | Mean (%) | St. Dev. (%) | P(25) (%) | P(75) (%) | Mean/St. Dev. | N |
|-----------|------------|----------|--------------|-----------|-----------|---------------|-----|
| 0 - 30 | 1.393 | 0.953 | 5.036 | -2.231 | 3.851 | 0.189 | 60 |
| 30 - 50 | 0.840 | 0.426 | 5.094 | -2.113 | 3.459 | 0.084 | 158 |
| 50 - 100 | 0.973 | 0.666 | 5.276 | -1.831 | 3.541 | 0.126 | 233 |

Notes: each panel of 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. A score equal to zero refers to stocks for which Bloomberg does not assign a score. Portfolios are set up so that the 0-30 portfolio consists of all the stocks with an ESG score greater than or equal to zero and lower than 30. 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.

5. Empirical strategy

We estimate three types of portfolios accounting for ESG dimensions in three different ways and thus corresponding to different ESG characterizations: the first uses only prior ESG screening (with different levels of tightness) to exclude stocks up to a certain level of ESG score with no guarantee on the resulting portfolio ESG score, the second uses a constraint in the optimization so as to reach a portfolio ESG-target with no guarantee on the ESG-score level of the stocks included in the optimal portfolio, the third combines features of both so as to obtain an optimal portfolio that on one hand reaches an ESG-target, on the other it does not include stocks whose ESG score is below a minimum level. Main features of the three strategies are summarized in Table 3.

Formally, the first results from prior screening of the sample based on ESG-score level and optimization of residual risk with no ESG constraints based on (16); the second is obtained from an unscreened sample by minimizing residual risk with ESG-score constraint as in (11), while the third optimizes with an ESG constraint as in (11) yet over a slightly screened sample.

Table 3. ESG-compliant portfolios: strategies at comparison

| | Prior ESG-screening | ESG-score constraint in optimization |
|------------|----------------------------|---|
| Strategy 1 | yes | no |
| Strategy 2 | no | yes |
| Strategy 3 | yes (mild) | yes |

All three portfolios require specification of a desired level of systemic risk, additionally: the first requires specification of an ESG-score level for screening, the second requires specification of a desired portfolio average ESG-score, and the third requires both specification of a desired portfolio average ESG-score and a low level of ESG screening of the sample. In the following we explain how we set these levels, robustness tests over these choices are presented in Section 8.

The different values for systemic risk and ESG screening threshold/target are meant to represent portfolios attainable by investors, which can be used as the so called Model Portfolios by the financial industry (Table 4). Specifically, beta can assume values 0.5, 1, and 1.5 so as to represent a defensive portfolio, a market tracking portfolio, and an aggressive portfolio respectively. As for the screening threshold we consider three exclusion levels (ESG scores ≥ 20 , ≥ 40 , ≥ 50) that are consistent with the ESG-score distribution of the dataset (Table 2) and correspond to an increasing attention towards sustainable investments (weak, intermediate, high respectively), whereby we take 50 as representative of the upper class since higher scores (e.g. ≥ 60) would imply the impossibility to find, at many times t , optimal portfolios when implementing the screening. Similarly, as for the ESG score target, we identify preferences for increasing levels of average portfolio ESG score that we take as representative of the classes in Table 2 (20, 40, 50). As a result, we obtain 9 portfolios given by combinations of desired levels of beta and ESG screening threshold/target. As for the level of minimum screening to obtain the third type of portfolio, we take 20.

Table 4. Portfolios attainable: possible combinations of systemic risk and ESG-compliance

| Strategy 1 | | | |
|----------------------------|---------------|---------------------------|-------------------------|
| Screening threshold | ≥ 20 | ≥ 40 | ≥ 50 |
| ESG target | - | - | - |
| $\beta = 0.5$ (defensive) | low exclusion | medium exclusion | high exclusion |
| $\beta = 1$ (mkt tracking) | low exclusion | medium exclusion | high exclusion |
| $\beta = 1.5$ (aggressive) | low exclusion | medium exclusion | high exclusion |
| Strategy 2 | | | |
| Screening threshold | - | - | - |
| ESG target | 20 | 40 | 50 |
| $\beta = 0.5$ (defensive) | low ESG | medium ESG | high ESG |
| $\beta = 1$ (mkt tracking) | low ESG | medium ESG | high ESG |
| $\beta = 1.5$ (aggressive) | low ESG | medium ESG | high ESG |
| Strategy 3 | | | |
| Screening threshold | - | ≥ 20 | ≥ 20 |
| ESG target | - | 40 | 50 |
| $\beta = 0.5$ (defensive) | - | low exclusion; medium ESG | low exclusion; high ESG |
| $\beta = 1$ (mkt tracking) | - | low exclusion; medium ESG | low exclusion; high ESG |
| $\beta = 1.5$ (aggressive) | - | low exclusion; medium ESG | low exclusion; high ESG |

Notes: The table represents, for each strategy, features of portfolios resulting from combinations of systemic risk (β) and ESG screening threshold/target.

Note that we allow shorting 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).¹²

¹² 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.

The Sharpe ratio for portfolio p is calculated as the ratio between the portfolio mean excess return μ and its standard deviation σ :¹³

$$SR_p = \frac{\mu}{\sigma} \quad (17)$$

Our final aim is to investigate the relation between portfolio Sharpe ratio and the desired level of portfolio systemic risk and ESG score and to compare this measure between the three optimal portfolio strategies.

6. Results

We start by comparing the risk-adjusted performance of the two philosophically farthest strategies to ESG-compliant portfolio, i.e. screening the investment set based on ESG scores before optimizing (Section 6.1) vs. constraining in terms of ESG while optimizing (Section 6.2). Finally, we propose a third strategy (Section 6.3) combining features of both by optimizing with an ESG constraint over a slightly screened sample.

For each strategy, we determine, for each month of the dataset, the optimal weights of portfolios: for the first two strategies we estimate 9 optimal portfolios characterized by the combination of different desired levels of portfolio beta (0.5, 1, 1.5) and portfolio ESG screening threshold/target score (20, 40, 50), while for the latter mixed strategy we estimate 6 optimal portfolios corresponding to a low screening threshold (20), the desired levels of portfolio beta (0.5, 1, 1.5) and two portfolio ESG score constraint (40, 50) reasonably consistent with a prior screening of 20. Then we calculate the out-of-sample realized return in the next month:¹⁴ for each portfolio we obtain a time series of realized returns that we use to calculate portfolio performance by means of the Sharpe ratios. Robustness tests on the above-defined ESG scores and different performance measures are presented in Section 8.

6.1 Portfolio optimization over an ESG screened sample

The first strategy, which is widely used in the industry, consists in accounting for the ESG dimension by which implementing first a negative screening strategy on the investment set and then using an optimization model. As for the choice of the latter, given the computational advantages stressed in Section 3.2, we adopt model (16) that minimizes residual risk with a specific level of systemic risk.

Table 5 reports results for different combinations of systemic risk and different levels of screening. A main result over the whole period 2007-2022 clearly emerges: the higher the screening the higher the risk adjusted performance, except for one conservative portfolio (#2). Results point to light screening (≥ 20) performing overall worse than heavy screening (≥ 40 or ≥ 50), which likely singles out firms performing better also from an economic viewpoint. Thus, when taking a two-step approach, our results point to optimal portfolio performance being positively related to screening.

¹³ 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>).

¹⁴ Constraints on the level of beta and ESG, when it is the case, must be satisfied in each month.

From a sustainable finance perspective this strategy has, on one hand, the advantage of granting only the inclusion of stocks with the desired level of sustainability, on the other the disadvantage of an unknown (since unconstrained) sustainability level in the final optimal portfolio.

Table 5. Optimal portfolio performance over a screened sample (no ESG target constraint)
Whole period 2007-2022

| #P | ESG screening score | β | Mean | St.Dev. | SR |
|----|---------------------|---------|--------|---------|--------|
| 1 | ≥ 20 | 0.5 | -0.013 | 4.772 | -0.003 |
| 2 | ≥ 40 | 0.5 | -0.037 | 4.660 | -0.008 |
| 3 | ≥ 50 | 0.5 | 0.041 | 4.537 | 0.009 |
| 4 | ≥ 20 | 1 | -0.032 | 5.951 | -0.005 |
| 5 | ≥ 40 | 1 | -0.006 | 5.877 | -0.001 |
| 6 | ≥ 50 | 1 | 0.200 | 5.643 | 0.036 |
| 7 | ≥ 20 | 1.5 | -0.050 | 7.410 | -0.007 |
| 8 | ≥ 40 | 1.5 | 0.025 | 7.457 | 0.003 |
| 9 | ≥ 50 | 1.5 | 0.360 | 7.386 | 0.049 |

Notes: #P indicates the progressive number of portfolios and screening \geq 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.

6.2 Portfolio optimization over an unscreened sample with an ESG constraint

The second strategy, consists in accounting for the ESG dimensions by introducing an ESG average score constraint in the optimization model. Given the computational advantages stressed in Section 3.2, we adopt model (11) that minimizes residual risk with a desired level of portfolio beta and ESG score.

Table 6 reports results for different combinations of systemic risk and different levels of portfolio ESG target score. Two main 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. For example, when beta is equal to 1, the Sharpe ratio of the portfolio with an average score of 20 is 0.012, it decreases to -0.001 when portfolio score is 30 and becomes -0.008 when the ESG score is 50. The same monotonicity is true for defensive portfolios (with beta equal to 0.5) and for aggressive ones (with beta equals to 1.5). Second, when keeping the ESG score constant, we observe a negative relationship between systemic risk and performance. 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), which is the only one in the literature implementing the same strategy, highlights 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, whereas in our sample the

relationship is convex (Table 2), and we do not observe such improvement in optimal portfolio performance (Table 6). This might be due to the model that must satisfy an equality constraint on ESG score, which requires taking short positions on low (or no) rated stocks that are characterized by a higher risk-return ratio, that stocks belonging to an intermediate rating class.

From a sustainable finance perspective this strategy has, on one hand, the advantage of granting an optimal portfolio consistent with a target level of sustainability, on the other the disadvantage that such an average portfolio ESG score may be obtained by including also stocks with a very low level of sustainability.

Table 6. Optimal portfolio performance for different levels of desired beta and ESG score - Whole period 2007-2022, unscreened sample

| #P | β | ESG score constraint (θ) | Mean | St.Dev. | SR |
|----|---------|-----------------------------------|--------|---------|--------|
| 1 | 0.5 | 20 | 0.089 | 4.928 | 0.018 |
| 2 | 0.5 | 40 | 0.008 | 4.835 | 0.002 |
| 3 | 0.5 | 50 | -0.033 | 4.874 | -0.007 |
| 4 | 1 | 20 | 0.074 | 5.971 | 0.012 |
| 5 | 1 | 40 | -0.008 | 5.885 | -0.001 |
| 6 | 1 | 50 | -0.049 | 5.913 | -0.008 |
| 7 | 1.5 | 20 | 0.058 | 7.271 | 0.008 |
| 8 | 1.5 | 40 | -0.024 | 7.194 | -0.003 |
| 9 | 1.5 | 50 | -0.064 | 7.213 | -0.009 |

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.

6.3 Portfolio optimization with an ESG constraint over a marginally screened sample

Given the shortcomings of the previous two strategies, the third one consists in accounting for the ESG dimensions by both screening the sample and introducing an ESG average score constraint in the optimization model. The idea is of reaching an optimal portfolio with a target ESG score, including only stocks with a minimum level of sustainability, and for this reason the original investment set is only slightly screened (i.e. ≥ 20).

We screen each month the sample by excluding stocks with ESG score lower than 20 and we use model (11) with target scores of 40 and 50, obtaining 6 optimal portfolios. Results, reported in Table 7, highlight that the higher the target, the better the SR and they can be usefully compared with those obtained by the two previous strategies.

Specifically, when comparing with the screening strategy without any target ESG portfolio score (Section 6.1), for comparability we can look at portfolios based on the same level of screening of 20, i.e. portfolios #1,4,7 in Table 5. It appears that, for each level of systemic risk, the absence of an ESG target constraint lowers SR, which are aligned to those of portfolios #1,3,5 in Table 7 that correspond to the lowest ESG target. When comparing with the same optimization problem implemented on an unscreened sample

(Table 6), we can compare each portfolio in Table 7 with portfolios 2,3,5,6,8,9 in Table 6 respectively. It clearly emerges that, for each level of beta, the sample screening, although mild, reverses the relationship: the higher the target ESG score, the higher the optimal portfolio performance.

These comparative results can be explained by the convex relationship observed in the investment set between ESG score and the ratio mean/standard deviation of returns. In fact, a mild negative screening excludes stocks characterized by a comparatively high ratio (Table 2, Panel A, first line) and, if intermediate ESG portfolio scores are targeted, portfolio will be mostly long on stocks with the lowest mean/standard deviation ratio (Table 2, Panel A, second line) whereas if highest ESG portfolio scores are targeted, portfolio will be mostly long on stocks with the highest mean/standard deviation ratio (Table 2, Panel A, third line).

Table 7. Optimal portfolio performance (with ESG score constraint) over a slightly screened sample - Whole period 2007-2022

| #P | ESG screening score | β | ESG score constraint (θ) | Mean | sd | SR |
|----|---------------------|---------|-----------------------------------|--------|-------|--------|
| 1 | ≥ 20 | 0.5 | 40 | -0.006 | 4.707 | -0.001 |
| 2 | ≥ 20 | 0.5 | 50 | 0.053 | 4.698 | 0.011 |
| 3 | ≥ 20 | 1 | 40 | -0.028 | 5.856 | -0.005 |
| 4 | ≥ 20 | 1 | 50 | 0.031 | 5.791 | 0.005 |
| 5 | ≥ 20 | 1.5 | 40 | -0.050 | 7.301 | -0.007 |
| 6 | ≥ 20 | 1.5 | 50 | 0.009 | 7.202 | 0.001 |

Notes: #P indicates the progressive number of portfolios and screening \geq 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.

7. Which is the best strategy for ESG-compliant portfolios on average and over time?

When comparing the three strategies over the whole period analysed, results in Tables 5, 6 and 7 support the following relationships between the specific ESG strategies and their performance: a) setting up ESG-compliant optimal portfolios based on prior ESG screening only implies a positive relationship between the optimal portfolio performance and the screening threshold; b) obtaining ESG-compliant optimal portfolios based only on a target ESG constraint at the optimization level, implies a negative relationship between the optimal portfolio performance and the target ESG level; c) setting up ESG-compliant portfolios by a combination of the two strategies (both prior screening, albeit light, and a target ESG constraint at the optimization level) reverses the previous result: the higher the target ESG score, the higher the optimal portfolio performance.

In sum, optimization after screening (1st strategy) implies a superior risk-adjusted performance only with heavy screening (>50). Accounting for ESG while optimizing (2nd strategy), returns portfolios with a performance that worsens as the target ESG level increases. By contrast, optimizing with an ESG constraint

after screening (3rd strategy) with a low threshold (20) implies portfolios with a performance that increases as the target ESG level increases. To be noted that these results, which hold for each level of target systemic risk, are driven by the convex relationship between ESG scores and the risk-reward relation of the initial dataset.

Now the question is whether results change when focusing on shorter subperiods and, if so, whether they change over the financial cycle (e.g. in a procyclical vs anticyclical manner). To this end in this Section, we compute rolling Sharpe ratios, with window width equal to 18 months and different levels of systemic risk (β). Since they do not show relevant differences, for reasons of space in Figure 1 we represent only the case of beta equal to 1 (other cases available upon request). In commenting results we will focus on the period after 2015, where the market is characterized by a greater ESG awareness following the publication of the Agenda 2030.

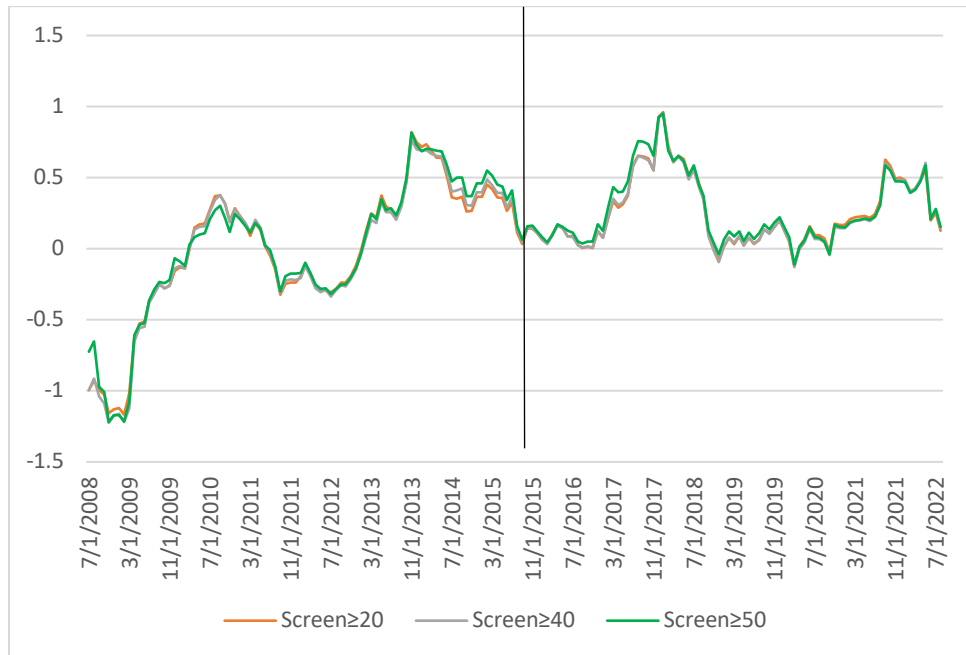
Panel a in Figure 1 plots rolling Sharpe ratios for the first strategy: optimal portfolios based on heavy screening (ESG score greater or equal 50) tend to overperform other portfolios most of the time, although in the period 2020-2022, portfolios performances are rather aligned and do not seem to be driven by the screening threshold. The latter might be explained by the fact that both the Covid-19 pandemic and the greater maturity of the ESG market have led the market to a new normal, characterized by a convergence in the performance of portfolios of different shades of ESG.

Panel b in Figure 1 plots rolling Sharpe ratios of the second strategy: rolling Sharpe ratios of portfolios with the highest ESG score (50) seem to reflect market phases being very close to/higher than Sharpe ratios of other portfolios in bullish market period such as 2017 (when Sharpe ratio of all portfolios is increasing), and underperforming in periods of constant/bear market such as 2018-2019 (when Sharpe ratio of all portfolios is almost constant or decreasing). Finally, in the period 2020-2022, when most stocks in the sample have a high ESG score, high-ESG portfolios overperform even when all Sharpe ratios are rapidly declining. Probably, in this latter period, a stronger awareness and demand for ESG assets is causing their performance to improve.

Finally, Panel c in Figure 1 plots rolling Sharpe ratios of the latter strategy. Portfolios performance is almost overlapping regardless of the market phase; hence, relative portfolio performance does not show procyclicality features as in the screening before optimizing strategy (Figure 1, Panel a). However, in 2021-2022 characterized by a fast-increasing awareness of ESG dimensions in financial decisions, the portfolio with the highest ESG target score slightly overperforms as in the optimizing without screening strategy (Figure 1, Panel b).

Figure 1. Portfolios' rolling Sharpe ratio for different ESG strategies

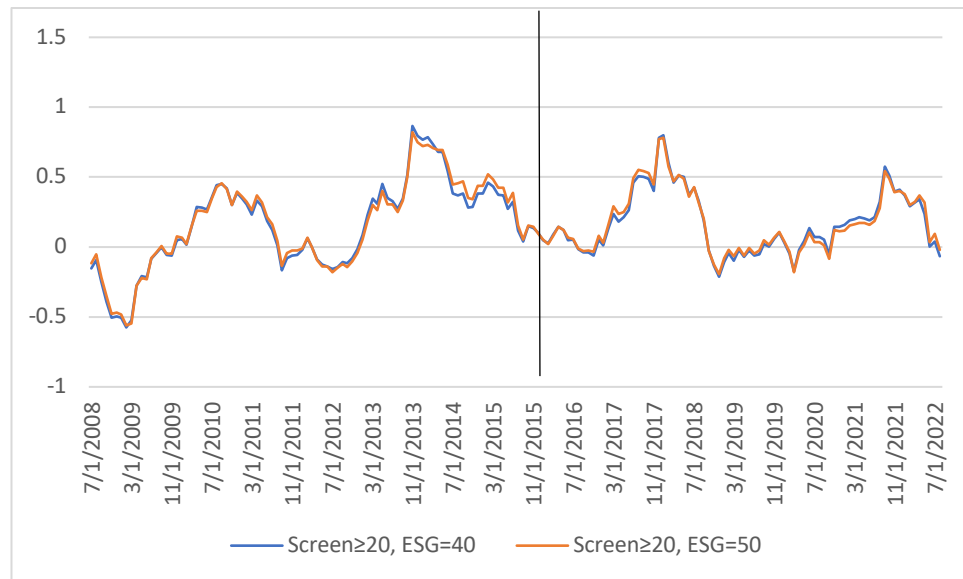
a) Portfolio optimization over an ESG screened sample



b) Portfolio optimization over an unscreened sample with ESG constraint



c) Portfolio optimization with ESG constraint over a marginally screened sample



Notes: each subfigure represents the Sharpe ratio for $\beta=1$ and for different ESG levels (either screening thresholds or optimization constraints or both). Rolling window width = 18 months. The vertical line, corresponding to January 1st 2016, represents the coming into force of the UN 2030 Agenda.

To sum up, when focusing on the period from 2015 following the publication of the UN 2030 Agenda, results show that the relative performance of optimal portfolios shows mild procyclicality only in strategies that account for ESG as a constraint in the optimization model, but such a relationship becomes countercyclical in the period 2020-2022 where the highest ESG portfolio overperforms even in a bearish market. By contrast, a strategy that accounts for ESG only by screening obtains quite similar performances across screening thresholds, even in the period following the Covid-19 pandemic outburst and does not show procyclicality features. Such a period is associated to a market in which investors are more aware and involved in sustainability issues, but the trend is not clear: it may result either in a superior performance of high ESG portfolios, or in new normal where there is a convergence in the performance of portfolios of different shades of ESG.

8. Robustness

This Section presents robustness tests to results presented in Section 6. We do so along two main lines: first we use alternative risk-adjusted measures with respect to the Sharpe ratio; second, we implement the three strategies described in Section 5 by including different levels of ESG screening and/or ESG target score.

Against its popularity because of its straightforwardness and simplicity, Sharpe ratio suffers of two main shortcomings: it does not satisfy the monotonicity property (Aumann and Serrano, 2008; Cheridito and Kromer, 2013), it is not appropriate in the presence of non-symmetrical distributions.

The violation of monotonicity can lead to situations in which an investor does not prefer a portfolio that produces a better result than another portfolio for every state of the world. To cope for this, we analyse

Conditional Sharpe ratio which is based on a coherent risk measure quantified by the Conditional Value at Risk (CVaR), i.e. the expected loss that exceeds VaR.¹⁵

As for alternative risk and performance measures that are useful in the presence of non-symmetrical distributions of returns, we compute the Calmar ratio and the Sortino ratio. As the (Conditional) Sharpe ratio, these measures consider the average excess return at the numerator of the ratio, however they differ for the risk measure used at the denominator: the Calmar ratio uses the maximum drawdown, i.e. the highest cumulated percentage loss incurred over the entire investment period; the Sortino ratio uses the square root of the lower partial moment of order two, i.e. an estimate of downside risk. Table 8 shows the alternative risk and performance measures for optimal portfolios set up with the three different strategies discussed in Section 5. By comparative inspection of Table 5 with Table 8 – Panel A, Table 6 with Table 8 – Panel B, and Table 7 with Table 8 - Panel C, we can conclude that results are qualitatively invariant.

Table 8. Optimal portfolio performance under alternative risk measures: Whole period 2007-2022

Panel A: optimization over an ESG-screened sample

| #P | β | Screen | Mean | CVaR | MDD | LPM2 | CSR | Calmar | Sortino |
|----|---------|-----------|--------|--------|--------|--------|--------|--------|---------|
| 1 | 0.5 | ≥ 20 | -0.013 | 13.316 | 78.561 | 13.718 | -0.001 | 0.000 | -0.004 |
| 2 | 0.5 | ≥ 40 | -0.037 | 13.006 | 78.026 | 13.042 | -0.003 | 0.000 | -0.010 |
| 3 | 0.5 | ≥ 50 | 0.041 | 11.607 | 73.069 | 11.468 | 0.004 | 0.001 | 0.012 |
| 4 | 1 | ≥ 20 | -0.032 | 16.071 | 82.156 | 20.174 | -0.002 | 0.000 | -0.007 |
| 5 | 1 | ≥ 40 | -0.006 | 15.570 | 80.413 | 19.162 | 0.000 | 0.000 | -0.001 |
| 6 | 1 | ≥ 50 | 0.200 | 13.452 | 75.090 | 16.056 | 0.015 | 0.003 | 0.050 |
| 7 | 1.5 | ≥ 20 | -0.050 | 19.095 | 85.694 | 29.593 | -0.003 | -0.001 | -0.009 |
| 8 | 1.5 | ≥ 40 | 0.025 | 18.416 | 85.043 | 28.400 | 0.001 | 0.000 | 0.005 |
| 9 | 1.5 | ≥ 50 | 0.360 | 17.138 | 79.162 | 25.369 | 0.021 | 0.005 | 0.071 |

Panel B: optimization with an ESG-score constraint θ over an unscreened sample

| #P | β | θ | Mean | CVaR | MDD | LPM2 | CSR | Calmar | Sortino |
|----|---------|----------|--------|--------|--------|--------|--------|--------|---------|
| 1 | 0.5 | 20 | 0.089 | 13.075 | 80.020 | 13.878 | 0.007 | 0.001 | 0.024 |
| 2 | 0.5 | 40 | 0.008 | 13.098 | 79.670 | 13.741 | 0.001 | 0.000 | 0.002 |
| 3 | 0.5 | 50 | -0.033 | 13.261 | 79.667 | 14.077 | -0.002 | 0.000 | -0.009 |
| 4 | 1 | 20 | 0.074 | 15.579 | 82.675 | 19.617 | 0.005 | 0.001 | 0.017 |
| 5 | 1 | 40 | -0.008 | 15.685 | 81.961 | 19.455 | -0.001 | 0.000 | -0.002 |
| 6 | 1 | 50 | -0.049 | 15.758 | 81.613 | 19.743 | -0.003 | -0.001 | -0.011 |
| 7 | 1.5 | 20 | 0.058 | 18.458 | 85.314 | 27.704 | 0.003 | 0.001 | 0.011 |
| 8 | 1.5 | 40 | -0.024 | 18.437 | 84.666 | 27.591 | -0.001 | 0.000 | -0.004 |
| 9 | 1.5 | 50 | -0.064 | 18.510 | 84.349 | 27.898 | -0.003 | -0.001 | -0.012 |

¹⁵ We take the 95% VaR calculated on historical basis as the reference.

Panel C: optimization with an ESG-score constraint θ over a mildly screened sample

| #P | β | θ | Screen | Mean | CVaR | MDD | LPM2 | CSR | Calmar | Sortino |
|----|---------|----------|-----------|--------|--------|--------|--------|--------|--------|---------|
| 1 | 0.5 | 40 | ≥ 20 | -0.006 | 12.713 | 77.724 | 13.061 | 0.000 | 0.000 | -0.002 |
| 2 | 0.5 | 50 | ≥ 20 | 0.053 | 12.381 | 76.495 | 12.693 | 0.004 | 0.001 | 0.015 |
| 3 | 1 | 40 | ≥ 20 | -0.028 | 15.505 | 81.355 | 19.226 | -0.002 | 0.000 | -0.006 |
| 4 | 1 | 50 | ≥ 20 | 0.031 | 15.137 | 79.822 | 18.360 | 0.002 | 0.000 | 0.007 |
| 5 | 1.5 | 40 | ≥ 20 | -0.050 | 18.534 | 85.014 | 28.421 | -0.003 | -0.001 | -0.009 |
| 6 | 1.5 | 50 | ≥ 20 | 0.009 | 18.154 | 83.682 | 27.127 | 0.001 | 0.000 | 0.002 |

Notes: beside the excess returns mean, each panel of the table shows alternative risk measures (CVaR, maximum drawdown - MDD - and lower partial moment of order two - LPM2 -) and the corresponding alternative performance measures (Conditional Sharpe ratio - CSR -, Calmar ratio and Sortino ratio).

In terms of robustness w.r.t. the ESG scores, in Table 9 we report results from optimization of: the first strategy with more screening thresholds, the second strategy with more levels of ESG target score, and the third strategy with a different light screening threshold. By comparative inspection of Table 5 with Table 9 – Panel A, Table 6 with Table 9 – Panel B, and Table 7 with Table 9 - Panel C, we can conclude that results are qualitatively invariant.

Table 9. Optimal portfolio performance with more levels of ESG screenings and/or ESG target score: Whole period 2007-2022

Panel A: optimization non-considering ESG over an ESG-screened sample

| #P | ESG screening score | 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 \geq 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.

Panel B: optimization with an ESG-score constraint θ over an unscreened sample

| #P | β | ESG score constraint (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.

Panel C: optimization with an ESG-score constraint θ over a mildly ESG-screened sample

| #P | ESG screening score | β | ESG score constraint (θ) | Mean | sd | SR |
|----|---------------------|---------|-----------------------------------|--------|-------|--------|
| 1 | ≥ 20 | 0.5 | 40 | -0.006 | 4.707 | -0.001 |
| 2 | ≥ 30 | 0.5 | 40 | -0.096 | 4.653 | -0.021 |
| 3 | ≥ 20 | 0.5 | 50 | 0.053 | 4.698 | 0.011 |
| 4 | ≥ 30 | 0.5 | 50 | 0.018 | 4.565 | 0.004 |
| 5 | ≥ 20 | 1 | 40 | -0.028 | 5.856 | -0.005 |
| 6 | ≥ 30 | 1 | 40 | -0.099 | 5.912 | -0.017 |
| 7 | ≥ 20 | 1 | 50 | 0.031 | 5.791 | 0.005 |
| 8 | ≥ 30 | 1 | 50 | 0.015 | 5.716 | 0.003 |
| 9 | ≥ 20 | 1.5 | 40 | -0.050 | 7.301 | -0.007 |
| 10 | ≥ 30 | 1.5 | 40 | -0.102 | 7.485 | -0.014 |
| 11 | ≥ 20 | 1.5 | 50 | 0.009 | 7.202 | 0.001 |
| 12 | ≥ 30 | 1.5 | 50 | 0.012 | 7.230 | 0.002 |

Notes: #P indicates the progressive number of portfolios and screening \geq 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.

9. Conclusions

The introduction of the ESG dimensions in setting up optimal portfolios has been becoming of uttermost relevance for the financial industry and, accordingly, the literature has been growing fast in recent years: theoretically it provides different approaches to the issue, empirically it is still inconclusive about the relationship between optimal portfolios financial performance and their ESG features.

The aim of this paper is to compare the performance of two philosophically different strategies to set up an ESG-compliant portfolio and to propose a third one resulting from a mixture of them. The first type of strategy, which is widely adopted in the industry, results from optimization on an ESG-screened sample, the second one is obtained by adding to the optimization problem a portfolio ESG-score constraint on an unscreened sample, the third one we propose takes pros of both, i.e. it optimizes with an ESG constraint (so as to reach a target) over a slightly screened sample (so as to eliminate only the worst companies in terms of ESG).

As for the choice of the optimization approach we follow the reformulation by Varmaz et al. (2022) of the a priori tri-criterion optimization that minimizes portfolio residual risk by imposing a desired level of portfolio average systemic risk and ESG (if necessary). The choice is made because of two main advantages of Varmaz et al. (2022) reformulation: it 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. Thus, we think this 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 in terms of target levels of systemic risk and ESG portfolio score, a useful feature to be aligned with the revision of the European Union's MiFID II directive.

Results are based on a sample starting from the 586 stocks that composed the EURO STOXX Index over the period January 2007 – August 2022, with Bloomberg ESG scores used to measure the ESG dimension of each stock. Two are the main results, which are robust with respect to the risk-adjusted measures used and the screening thresholds/targets taken.

First, the performance of an ESG-compliant portfolio depends both on the strategy taken (optimizing after screening, constraining optimization or an appropriate mixture) and the relationship between ESG scores and the risk-reward (monotone, convex, concave) of the initial investment set. In fact, optimization after screening (1st strategy) implies a superior risk-adjusted performance only with heavy screening. Accounting for ESG while optimizing (2nd strategy), returns portfolios with a performance that, for each level of systemic risk, worsens as the target ESG level increases. By contrast, optimizing with an ESG constraint after a mild ESG screening (3rd strategy) implies portfolios with a performance that, for each level of systemic risk, increases as the target ESG level increases. However, these results are driven by the convex relationship between ESG scores and the risk-reward relation of the initial dataset.

Second, when testing for the ESG-compliant portfolio that better perform over time, we find that the comparative performance of the three strategies does not change much over the financial cycle. In fact, by estimating rolling Sharpe ratios and focusing on the period following the publication of the UN 2030 Agenda,

results show that the relative performance of optimal portfolios shows mild procyclicality only in strategies that account for ESG as a constraint in the optimization model, but such a relationship becomes countercyclical in the period 2020-2022 where the highest ESG portfolio overperforms even in a bearish market. By contrast, a strategy that accounts for ESG only by screening obtains quite similar performances across screening thresholds, even in the period following the Covid-19 pandemic outburst. Such a period is associated to a market in which investors are more aware and involved in sustainability issues, but the trend is not clear: it may result either in a superior performance of high ESG portfolios, or in new normal where there is a convergence in the performance of portfolios of different shades of ESG.

In terms of policy implications, investors and asset managers must be aware that optimal portfolios are characterized by a return-risk reward that to some extent reflects the one of the initial investment set (monotone, convex, concave). In fact, in the original contribution by Varmaz et al. (2022), based on a sample consisting of stocks from the US S&P 500 Index and ESG scores from Refinitiv Datastream, the model shows an increasing performance as the overall ESG score of the optimal portfolio increases, consistently with a monotonically increasing relation between the return-risk reward and the ESG score in their investment set. On the contrary, in our sample such a relation is convex with higher profitability in correspondence of both low/absent ESG scores and top ESG scores and lower profitability for stocks with intermediate ESG scores. Hence our resulting optimal portfolios have to sacrifice performance in order to minimize residual risk and have high levels of ESG.

To be noted that, the third strategy we propose, which combines advantages of both screening and optimization with an ESG constraint allows sustainable investors to do well by doing good in the presence of both a convex and a monotone investment set. Thus it can be particularly interesting for the financial industry and the real economy since it can attract a larger pool of investors towards ESG-compliant optimal portfolios.

Future developments may include 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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