Portfolio optimization with green assets

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Abstract

The aim of this work is to show the relationship between the economic and the environmental performance of a portfolio of European stocks. To do so we use the data from STOXX Europe 600 for the period 03/01/2007 30/12/2019 and the Environmental score (E score) as a proxy of the environmental performance of each stock. In the mean-CVaR space, we derive the efficient frontier maximising for each target E score the Mean-to-CVaR (MtC). We find a trade-off between portfolio performance and E score. We show that portfolios with higher E score have lower CVaR and lower expected return. Above a certain threshold E score only inefficient portfolios are obtained. This holds true for all sectors except Energy, where portfolios with higher E score show higher risk.

Keywords: Climate change; Sustainable finance; Conditional Value at Risk; Portfolio optimization;

1 Introduction

At the start of 2020, sustainable investments amounted to 35.3 USD trillion in the markets of USA, Europe, Canada, Japan and Australasia, with an increase of 55% over the period 2016-2020. This heightened sensibility towards more responsible investments, in particular environmentally friendly, can be understood especially under the light of recent policy developments, such as the *Paris Agreement*, seeking an international agreement over the urgent measures to take in order to tackle the issues arising from global warming.

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In particular, the European Union has made of the fight against global warming one of its priorities with the *The European Green Deal*. In this plan, the financial sector has been deemed crucial in the green transition, for its key role in funding the new investments to face the new risks.

While most of the investors in responsible strategies are still institutional, accounting for 75% of the total investments, retailers are rapidly increasing their demand for responsible investment options as well. In a Morning Star Research, the vast majority of new fund offers in the European market in 2020 were broad ESG funds, with 13% of them being solely environmentally focused (Global Sustainable Investment Alliance 2020). According to a 2019 Morgan Stanley study, 85% of US individual investors surveyed were interested in sustainable investing, up 10% from 2017; among millennials, 95% were interested, up 9% from 2017.

Being the environmental concern perceived as the most compelling issue by investors and policymakers, the rest of this work focuses specifically on green investments.

The aim of this work is to empirically investigate the relationship between the environmental impact and the risk-return profile of an investment strategy. The features of this analysis are: the employment of the CVaR as a risk measure, due to its capability to better capture tail events and the use of the E score as a measure of the environmental effort of the portfolio.

We chose a portfolio selection model built in the in the Mean-to-CVaR (MtC) framework as proposed by Pagliardi, Lotfi, Paparoditis, and Zenios 2022. This choice is motivated by the non-normal nature of returns, highlighted by the descriptive statistics performed on the data. For all of the stocks studied, we find significant skewness and high kurtosis, and we reject the Gaussian hypothesis in the Jarque-Bera test. The classical mean-standard deviation approach is not adequate to measure the true risk of the portfolio, since it might lead to the underestimation of the probability of more extreme events. Furthermore, the standard deviation is not a coherent risk measure as in Artzner, Delbaen, Eber, and Heath 1999.

We use as a risk measure the CVaR, defined as the expected loss given that it will be greater than the Value-at-Risk (VaR) since it is a coherent risk measure, can be easily linearized and, focusing only on the left tail of the distribution, is able to capture tail events[1].

To measure the environmental impact of a company the most widely used tool is the Environmetal, Social, Governance (ESG) score. Such scores are issued by several rating agencies and provide a synthetic measure of the company's performance in the environment, social and governance aspects. In our analysis we will rely on ESG scores, using the E pillar as a proxy of the environmental impact

[1]see Rockafellar and Uryasev 2002.

of a company. To measure the economic performance of a portfolio, we use the Mean-to-CVaR ratio, which is the counterpart of the Sharpe ratio in the mean-CVaR set-up; in addition, a comparison test between two ratios and two CVaRs as proposed by Pagliardi, Lotfi, Paparoditis, and Zenios 2022 is used.

In this framework, we build the Green MtC efficient frontier, by repeatedly maximising the ratio for each target E score, both for the no short sales and covered short positions allowed strategies. To take into account the possible effects deriving from exclusionary screening practices, the efficient frontier is calculated by removing the stocks with E score lower than the 20th (exclusionary screening strategy 1) and 30th (exclusionary screening strategy 2) percentile of the average E score distribution. Lastly, we calculate the Green MtC frontiers for all the sectors, to explore the possibility of a sector-specific relationship between environmental and economic performance.

First, observing the E score Mean-to-CVaR frontiers, it is possible to notice how in all the cases there is a trade-off between portfolio performance and E score. The loss of performance is non-linear with the score: the higher the starting E score the higher will be the loss in terms of Mean-to-CVaR to further increase it. The trade-off is more pronounced in the case of no short sales allowed. The most favourable trade-off is achieved in the covered short position on the full sample strategy.

Examining the expected return and CVaR separately, we find that in most cases, the higher the E score, the lower the CVaR and expected return of the portfolio. However, this holds true until a certain threshold E score is reached, after which we observe a reduction in return and an increase in CVaR. Such E score is lower when imposing restrictions to the maximization process, such as reducing the pool of assets and not allowing for short positions. For one case, the maximization on the dataset removing the worst 20% performing and allowing for covered short positions, it is true the contrary, with higher scores leading to higher returns and CVaRs.

The results of the analysis by sector are in accordance with what was highlighted before: there is a trade-off -different in magnitude for each sector- between portfolio performance and E score. For all sectors -except for Energy- the pair CVaR-return decreases up to a certain E score, beyond which only inefficient portfolios are found. This might be a sign of a sector-specific relationship between E score and risk.

These findings have some implications for environmentally motivated investors, who need to trade off part of the portfolio performance in order to have their E score requirements met. The strategy offering the best trade-off is the maximization of the MtC allowing for short selling on the full sample. A possible drawback is that in this case even for high E scores some lower-graded stocks are bought and some higher-graded stocks are sold, so the real environmental impact of the strategy might be more nuanced to assess. In addition, investors should be careful when choosing the benchmark E score of their portfolio, since after a certain value only inefficient allocations are found.

1.1 Related literature

This work is placed in the literature investigating the relationship between responsible investing and financial performance, in particular approaches the problem from a more risk-focused perspective.

The evidence regarding the effects of general ESG integration on asset returns is mixed: some studies find a positive correlation between ESG performance and profitability, while others highlight a negative correlation. Krüger 2015 analyzes the effect on daily CARs of positive and negative events concerning firms' corporate and social responsibilities. While negative news cause negative CARs, the impact of positive news is not necessarily positive. A similar analysis is conducted by Flammer 2013, where she shows a positive correlation between CARs and environmentally responsible initiatives; furthermore, the author illustrates how the shareholder reaction towards eco-harmful events increases over time, while the reaction towards eco-friendly initiatives decreases. Derwall, Guenster, Bauer, and Koedijk 2005, evaluating the environmental performance of the portfolio using scores built on the concept of "eco-efficiency"[2] found evidence that the higher-rated portfolio performs better than its lower-rated counterpart.

Opposite pieces of evidence are found by Bolton and Kacperczyk 2021, who focus in particular on the returns of high CO_2 emitting companies; they prove that indeed high carbon emitting companies are treated like sin stocks (as in Hong and Kacperczyk 2009): they have lower prices and grant higher returns, due to a carbon premium, and institutional investors substantially underweight them in their portfolios. Rohleder, Wilkens, and Zink 2022 and De Angelis, Tankov, and Zerbib 2023 show how the price of the most carbon-intensive firms is pushed down due to selling pressure by green investors. Similar evidence is found by Ilhan, Sautner, and Vilkov 2021 in the option market, where a higher price for protection against downside tail risk is asked in the case of firms with carbon-intense business model.

Other authors build equilibrium models, such as Zerbib 2022, who builds an equilibrium model with partial segmentation and heterogeneous preferences, where the presence of sustainable investors induces higher returns on brown assets via a taste premium and two exclusion premia.Pedersen,

[2]interpreted as the economic value a company adds relative to the waste it generates when creating it.

Fitzgibbons, and Pomorski 2021 who derive an ESG-adjusted CAPM, allowing for the presence of different types of investors with different attitudes toward ESG and information embedded in them, or Pástor, Stambaugh, and Taylor 2021, De Angelis, Tankov, and Zerbib 2021. In all these studies, under particular model specifications -such as the preferences of the investors towards E scores- greener stocks have lower returns than those of their brown counterparts. Lastly, Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens 2020, Faccini, Matin, and Skiadopoulos 2023, Hsu, Li, and Tsou 2023 applying portfolio sorting methodologies find that brown firms outperform the green ones.

The structure of the article is as follows: In Section 2 we discuss in detail the methodological aspects, in particular the CVaR, how to maximize the Mean-to-CVaR ratio, a brief description of how the data are simulated, and lastly how the hypothesis tests are calculated. In Section 3 after a brief description of the characteristics of the dataset used, the main empirical results are presented. Lastly in Section 4 the conclusions and in Appendix all the results and graphs not shown in the precedent chapters are available.

2 Model set-up

In this section, we develop the portfolio selection model with the inclusion of environmental constraint. We develop the efficient frontier and obtain the optimal allocation leveraging on MtC-constrained optimization in Pagliardi, Lotfi, Paparoditis, and Zenios 2022.

2.1 The CVaR

The definition of CVaR, conditional value at risk, is strictly tied to that of VaR, value at risk: given a level of probability α, the VaR is the lowest amount γ such that the loss will not exceed that value with probability α; the CVaR is the expected value of the loss given that it will exceed the VaR.

The loss function is *f(x,y)*, where x is the decision vector, -in the case of the portfolio optimization problem are the weights associated with each instrument-, and y, the vector of uncertainties, e.g. a vector of future returns. For each x, the loss function has a probability distribution function *p(y)* induced by y.

Being $\Psi(x, \gamma)$ is the cumulative distribution function of the loss associated with x, VaR_α of a loss *f(x,y)* is defined as:

$$VaR_\alpha = \min\{\gamma \in \mathbb{R} : \Psi(x,\gamma) \geq \alpha\}$$

and the $CVaR_\alpha$

$$CVaR_\alpha = (1-\alpha)^{-1} \int_{f(x,y) \geq VaR(x)_\alpha} f(x,y)p(y)\,dy$$

It is fundamental the use of the following function, which behaves as the CVaR function but is easier to handle:

$$F_\alpha(x,\gamma) = \gamma + (1-\alpha)^{-1} \int_{y \in \mathbb{R}^m} [f(x,y) - \gamma]^+ p(y)\,dy$$

The function $F_\alpha(x,\gamma)$ has nice properties, such as being continuously differentiable and convex with respect to γ. The CVaR can be obtained by minimizing this function, without having to calculate previously the VaR, which is now obtained as a byproduct of said minimization.

$$CVaR_\alpha(x) = \min_{\gamma \in \mathbb{R}} F_\alpha(x,\gamma)$$

In order to solve the integral in the previous formulation of $F_\beta(x,\gamma)$, some numerical approximations are needed, such as sampling from the probability density function of y, leading to the following approximated function:

$$\widetilde{F}_\alpha(x,\gamma) = \gamma + \frac{1}{q(1-\alpha)} \sum_{k=1}^{q} [f(x,y_k) - \gamma]^+$$

$\widetilde{F}_\alpha(x,\gamma)$ is still linear with respect to α, convex and can be minimized in terms of a linear programming problem.

2.2 The Mean-to-CVaR portfolio

To calculate the CVaR of a portfolio, the CVaR must be reformulated as follows:

$$CVaR_\alpha(\widetilde{r}_p) = -\mathbb{E}[\widetilde{r}_p \mid \widetilde{r}_p \leq \gamma]$$

with α being the confidence level, γ the VaR for such α and $\widetilde{r}_p$ a random portfolio return.

The auxiliary function from Rockafellar and Uryasev 2002 becomes:

$$F_\alpha(\widetilde{r}_p, \gamma) = \gamma + \frac{1}{1-\alpha}\mathbb{E}[\max\{-\widetilde{r}_p - \gamma, 0\}]$$

and the CVaR is again obtained minimizing $F_\alpha(\widetilde{r}_p, \gamma)$.

Going back to the portfolio selection model, the investor is faced with the well-known problem of deciding how much to invest in the risky securities and how much in the risk-less asset.

The portfolio is the following:

$$\widetilde{r}_c = y\widetilde{r}_p + (1-y)r_f \tag{2.1}$$

$\widetilde{r}_p = \widetilde{r}^\top x$ is the return of the portfolio composed by only risky securities, with $\widetilde{r}$ being the random vector of returns and x the weights for each instrument; r_f the risk-free rate and $y \in (0,1)$ how much is invested in the risky option.

The CVaR of the portfolio is:

$$CVaR_\alpha(\widetilde{r}_c) = yCVaR_\alpha(\widetilde{r}_p) + (1-y)r_f \tag{2.2}$$

To get the formulation of the portfolio in terms of the Mean-to-CVaR ratio, 2.2 must be solved for y and then substituted in 2.1. The result is the following:

$$\mathbb{E}[\widetilde{r}_c] = (1 + \frac{\mathbb{E}[\widetilde{r}_p - r_f]}{CVaR_\alpha(\widetilde{r}_p) - r_f})r_f + \frac{\mathbb{E}[\widetilde{r}_p - r_f]}{CVaR_\alpha(\widetilde{r}_p - r_f)}CVaR_\alpha(\widetilde{r}_c)$$

The coefficient of the second term of the previous equation is the Mean-to-CVaR ratio:

$$MtC_\alpha = \frac{\mathbb{E}[\widetilde{r}_p - r_f]}{CVaR_\alpha(\widetilde{r}_p - r_f)}$$

Maximizing this ratio is therefore possible to obtain the tangency portfolio.

Like the Sharpe ratio $S_p = \frac{\mathbb{E}[\widetilde{r}_p - r_f]}{\sigma(\widetilde{r}_p - r_f)}$, the MtC is a measure of the risk that the investors need to bear for each additional unit of expected return. The difference between the two ratios is given by the term in the denominator, i.e. the risk measure, which is the standard deviation in the Sharpe ratio whereas the CVaR in the MtC. This choice has several advantages: using volatility as a risk measure implies the normality of returns and does not allow us to differentiate between positive and negative deviations from the mean. The CVaR, instead, is able to better capture tail risk since it focuses on the left tail of the distribution and does not necessarily depend on any prior assumptions on the distribution of returns.

The Mean-to-CVaR maximization problem can be formulated in terms of linear programming; here the formula in the case of no short sales allowed:

$$\max_{x' \in \mathbb{R}^n, u' \in \mathbb{R}^S, \gamma' \in \mathbb{R}} (\bar{r} - r_f e')^\top x'$$

$$s.t. \qquad \gamma' + \frac{1}{S(1-\alpha)} e^\top u' = 1$$

$$-R_e x' - u' - e\gamma' \leq 0$$

$$e^\top x' > 0$$

$$u', x' \geq 0$$

where R_e is the $S \times n$ simulated matrix of the excess return, and e a n-dimensional vector of 1.

From the optimal solution to the previous optimization problem x'^*, the weights of the maximum Mean-to-CVaR portfolio are obtained using $x^* = \frac{1}{e^\top x'^*} x'^*$.

The proof is given in Pagliardi, Lotfi, Paparoditis, and Zenios 2022 Online Appendix.

2.3 E score integration

The most popular sustainable investment strategies in Global Sustainable Investment Alliance 2020 are E score integration and exclusionary screening. Through E score integration we include E metrics into the optimal allocation problem, while exclusionary screening is obtained by removing from the investable assets those with poor E score or those whose business activities are against the moral values of the investors (e.g. oil and coal companies are commonly classified under the excluded assets). In this work, we examine the effects on portfolio performance of both strategies.

The E score integration is obtained by adding an additional constraint to the MtC optimization problem: the overall E score of the portfolio, which is given by the E score of the single instrument times its weight, must be equal to a desired level of responsibility $\bar{E}$. The additional constraint is:

$$E^\top x = \bar{E}. \tag{2.3}$$

The allocation having the highest possible MtC while at the same achieving the E score of $\bar{E}$ is the result of the optimization described. The green MtC frontier is obtained by repeatedly maximising the MtC for different benchmark E scores, and shows how the portfolio performance varies with changes in the E score. To take into account the possible effects deriving from exclusionary screening practices, the efficient frontier is calculated by removing the stocks with E score lower than the 20th (exclusionary screening strategy 1) and 30th (exclusionary screening strategy 2) percentile of the average E score distribution.

2.4 Scenario Generation

All the calculations required by the models are performed using scenarios, which are realizations of a multivariate random variable representing the rate of return for the securities considered in building the portfolio. It is thus of particular importance the procedure used to estimate the scenarios since the validity and the accuracy of the model strongly depend on them.

In this work, all the scenarios are simulated using moving-block bootstrap, a non-parametric scenario generation technique as described in Kreiss and Lahiri 2012.

Supposing $\{X_t\}_{t\in\mathbb{N}}$ is a stationary weakly independent time series and $\{X_1, ..., X_t\}$ a collection of observations from the time series; choosing $b, 1 \leq b < n$ as number of observations in each block B and structuring the overlapping blocks as:

$$B_1 = (X_1, X_2, ..., X_b)$$
$$B_2 = (X_2, X_3, ..., X_{b+1})$$
$$...$$
$$B_N = (X_{n-b+1}, ..., X_n)$$

with $N = n - b + 1$ and supposing for simplicity that b divides n. This way $k = \frac{n}{b}$ blocks are extracted with replacement from the collection of blocks previously described and then concatenated following the selection order.

The efficacy of such techniques depends very much on the choice of the length of each block b; for $b = 1$ the moving-block bootstrap reduces to the simple bootstrap technique, and while there are sophisticated methods to choose the optimal block length, it is fairly common to choose $b = Cn^{\frac{1}{k}}$ for $k = \{3, 4\}$ and $C \in \mathbb{R}$.

The moving-block bootstrap is an efficient technique since it does not require finding a distribution that approximates well the data and allows for a huge number of scenarios; furthermore, it is able to retain a fair amount of the dependency structure, due to the fact that the observations are re-sampled in blocks of sequential data long enough that the correlation between the block and the data left outside is neglectable.

2.5 Hypothesis testing

Lastly, to add robustness to the analysis, we test whether the difference between two ratios MtC_0^* and MtC_1^* is statistically significant as in Pagliardi, Lotfi, Paparoditis, and Zenios 2022. The two ratios are obtained by maximising the Mean-to-CVaR for the same asset pool but for two different E scores E_0 and E_1. The hypothesis tested is:

$$H_0 : MtC_1^* - MtC_0^* = 0 \qquad vs \qquad H_1 : MtC_1^* - MtC_0^* > 0$$

using the statistic:

$$T_S = \widehat{MtC_1} - \widehat{MtC_0}$$

where $\widehat{MtC_0}$ and $\widehat{MtC_1}$ are

$$\widehat{MtC_j} = \frac{\bar{r}_j}{\widehat{CVaR_j}} \qquad j \in \{0, 1\}$$

$$\bar{r}_j = \frac{1}{S}\sum_{t=1}^{S} r_{j,t}, \qquad \widehat{CVaR_j} = \frac{1}{S(1-\alpha)}\sum_{t=1}^{S} r_{j,t}\mathbb{1}(r_{i,j} \le \widehat{\zeta}_{j,1-\alpha})$$

Under the null hypothesis and for $S \to \infty$ the test statistic is distributed as:

$$\sqrt{S}T_S \xrightarrow{d} N(0, \tau_0^2)$$

where τ_0^2 is defined as $\tau_0^2 = \underline{c}^\top \Sigma_r \underline{c}$, where

$$\underline{c} = \left(\frac{1}{CVaR_1}, -\frac{MtC^*}{CVaR_1}, -\frac{1}{CVaR_0}, \frac{MtC^*}{CVaR_0}\right)$$

$$\Sigma_r = \sum_{h=-\infty}^{\infty} Cov\left(R_t, R_{t+h}\right)$$

with the vector R_t defined as

$$R_t = \left(r_{1,t}, -\frac{1}{(1-\alpha)} r_{1,t} \mathbb{1} \cdot (r_{1,t} \leq \zeta_{1,1-\alpha}), r_{0,t}, -\frac{1}{(1-\alpha)} r_{0,t} \mathbb{1} \cdot (r_{0,t} \leq \zeta_{0,1-\alpha}) \right)^\top$$

The most computationally heavy part of this test is the estimation of Σ_r, which is done via overlapping block bootstrap.

The null hypothesis is rejected if $\sqrt{S} \cdot T_S \geq z_{1-\beta}$, $z_{1-\beta}$ being the $1-\beta$ quantile of the $N\left(0, \hat{\tau}_0^2\right)$ distribution.

Following the same procedure is possible to implement a test to compare two different CVaRs as well. The hypothesis test is as in the previously illustrated test:

$$H_0 : CVaR_1^* - CVaR_0^* = 0 \qquad vs \qquad H_1 : CVaR_1^* - CVaR_0^* > 0$$

In this case the test statistic is:

$$C_S = \widehat{CVaR}_1 - \widehat{CVaR}_0$$

Under the null hypothesis,

$$\sqrt{S} C_S \xrightarrow{d} N(0, \nu_0^2) \qquad as \qquad S \to \infty$$

with ν_0^2 being equal to $\underline{e}^\top \Sigma_r \underline{e}$, $\underline{e} = (0, 1, 0, -1)$ and Σ_r the same covariance matrix for the Mean-to-CVaR ratio test.

So the null is rejected if $\sqrt{S} C_S \geq z_{1-\beta}$, where $z_{1-\beta}$ is the upper $1-\beta$ percentage point of the $N\left(0, \widehat{\nu}_0^2\right)$; $\widehat{\nu}_0^2$ is the estimator of ν_0^2 obtaining estimating Σ_r using the same procedure described previously.

3 Empirical results

The first part of this chapter presents a brief analysis on the characteristics of the dataset, the rest is dedicated to the main findings of this work.

3.1 Dataset analysis

3.1.1 Stocks

To build the portfolio, 327 stocks from those forming the STOXX Europe 600 index are taken into consideration; the observations are from 03/01/2007 to 30/12/2019. The index takes into consideration the 600 most representative companies from European countries, from all the 11 industry sectors, as identified in Appendix A of the STOXX methodology guide Qontigo 2022: Technology, Telecommunications, Health Care, Financials, Consumer Discretionary, Consumer Staples, Industrials, Basic Materials, Energy, Utilities, Real Estate.

From the daily prices y_t, the daily log returns are calculated. Then, to study their behaviour some descriptive statistics are computed: mean, variance, skewness and kurtosis.

The mean is very close to 0 for all the stocks considered. Almost all the stocks considered present significant values for the skewness, in particular, the vast majority is negatively skewed, which indicates a distribution with a more pronounced left tail. Being most of the returns negatively skewed, investors are likely to expect frequent small gains but few large losses. Additionally, all the daily returns present a high value for the kurtosis, signally the presence of the so-called fat tails: the returns follow leptokurtic distributions, producing therefore more extreme values than those of a normal. Lastly, the Jarque-Brera normality test was performed: for all the studied returns the hypothesis of normality should be rejected.

3.1.2 E scores

We gather the E scores for the years 2007 to 2019. After cleaning the data we are left with 327 stocks for which we have availability of E scores. The E score is the E component of the ESG score, a synthetic measure of the company's environmental, social, and corporate governance performance, calculated using publicly available company-reported data. It is used as a proxy for the environmental preferences of investors.

In order to obtain the final score for each of the three pillars is divided into different categories, 10 in total; for the environmental valuations: resource use, emission and innovation.

For each category, a percentile rank-based score as follows:

$$score = \frac{n.\,of\,companies\,with\,worst\,value + \frac{n.companies\,same\,value\,included\,in\,current}{2}}{n.\,companies\,with\,a\,value}$$

Since each category has a weight associated, the score for each pillar is obtained by aggregating the scores calculated for the categories.

Looking at the distribution of the average E score for each stock, a longer left tail can be observed, indicating that mostly all companies have sufficient grading while those with poorer ratings have grades significantly lower than the average.

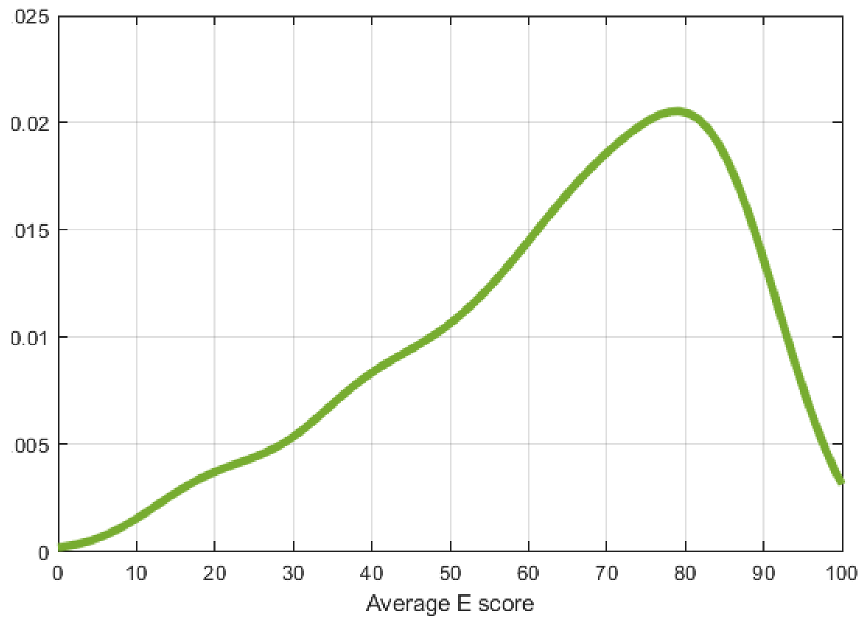

Figure 1: Average E score distribution

Studying the evolution over the years of the average score for each sector, a similar pattern of improvement can be observed in all of them; furthermore, some sectors, Real Estate, Utilities, Energy, Consumer Staples, and Basic Materials constantly performed better on average than the others.

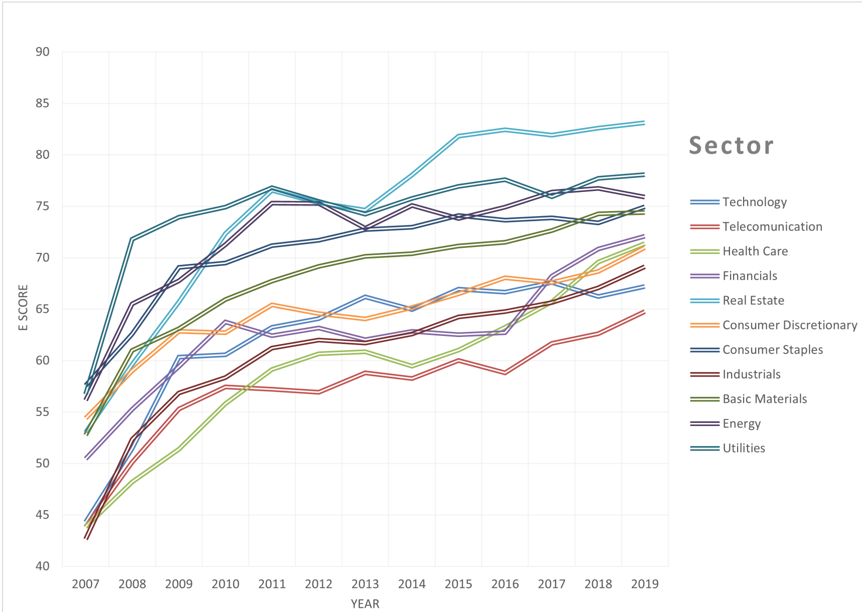

Figure 2: E score by sector

3.2 The MtC efficient frontier

The following frontiers have been obtained by repeatedly maximizing the MtC ratio considering a confidence level of $\alpha = 95\%$ and imposing different levels of the E score. First, the results for the no short sales case are presented. In Figure 3 the frontiers for the full dataset of the STOXX Europe 100 and the one obtained implementing the exclusionary screening strategy are plotted.

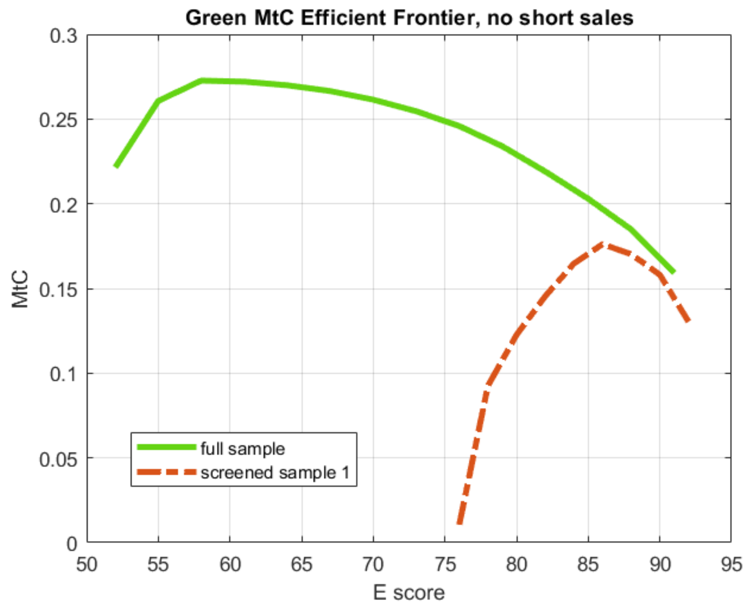

Figure 3: Green MtC efficient frontier for the complete STOXX Europe 100 dataset and for the exclusionary screening strategy 1, no short sales. Data from 2007-2019.

For the no short sales case, the maximum Mean-to-CVaR score is achievable for the E score of 58.7939, which is the E score of the market portfolio -obtained by solving the unconstrained Mean-to-CVaR optimization. Requiring a different E score pushes the strategy further from the highest achievable ratio: environment-concerned investors need therefore to trade portfolio performance in order to obtain higher scores. The loss of performance is not linear with the score: constraining the portfolio into having a score 3 points higher causes a MtC variation very small but significant (when tested at 99%) when passing from 58 to 61, of $-0,81\%$ passing from 61 to 64 while of $-8,92\%$ passing from 85 to 88. This is partially due to the fact that given the no short sales constraint, the only way to achieve a higher E score is to invest only in high E score stocks, losing this way all the benefits of diversification.

To analyze the effects of exclusionary screening practices, we study the frontier calculated for the dataset after removing the stocks with E score lower than the 20th percentile of the average E score distribution. It shows the same behaviour as the frontier for the full sample: scores too high or too low are detrimental to portfolio performance. The highest ratio is sensibly lower than the one calculated for the full sample: reducing the number of assets prevents the investor from reaping the benefits deriving from diversification.

Table 1: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score using the complete STOXX Europe dataset, no short sales. Data from 2007-2019.

E Score	**Return**	**CVaR**
91	0.0618	0.3885
88	0.0724	0.3919
85	0.0805	0.3966
82	0.0841	0.3842
79	0.0901	0.3849
76	0.0966	0.3928
73	0.1029	0.4042
70	0.1080	0.4129
67	0.1144	0.4292
64	0.1210	0.4483
61	0.1277	0.4695
58	0.1334	0.4890
55	0.1487	0.5706
52	0.1600	0.7225

Moreover, observing the pairs expected return-CVaR in Table 1, it is possible to notice how the portfolios with lower E scores present a profile of higher returns and higher CVaR, while portfolios with higher E scores present lower expected returns and lower CVaRs. When testing by consecutive pairs of the CVaRs the null hypothesis $CVaR_1 - CVaR_0 = 0$ is always rejected at 99%. Up to a certain threshold, requiring a higher E score reduces the return of the portfolio reducing at the same time the risk. Imposing very high scores though (from 85 to 91, in the full dataset case) increases the CVaR and lowers the expected return: such portfolios are in the inefficient part of the frontier.

The covered short positions allowed strategy is reported in Figure 5. We reach the same conclusions as the no short sales case. The frontier reaches its maximum for a higher E score and grants, for all E score, higher performance ratios; in this case, as well both lower and higher scores hinder the portfolio performance. The reduction in the MtC is still non-linear with respect to the increase in the E score, but the trade-off between portfolio performance and E score is less pronounced. The reduction in the MtC is very small but still significant when tested passing from 70 to 73, of $-0,12\%$ passing from 73 to 76 and of $-2,1\%$ passing from 88 to 91. The frontiers calculated with the exclusion screening strategies grant lower MtC for all E score studied.

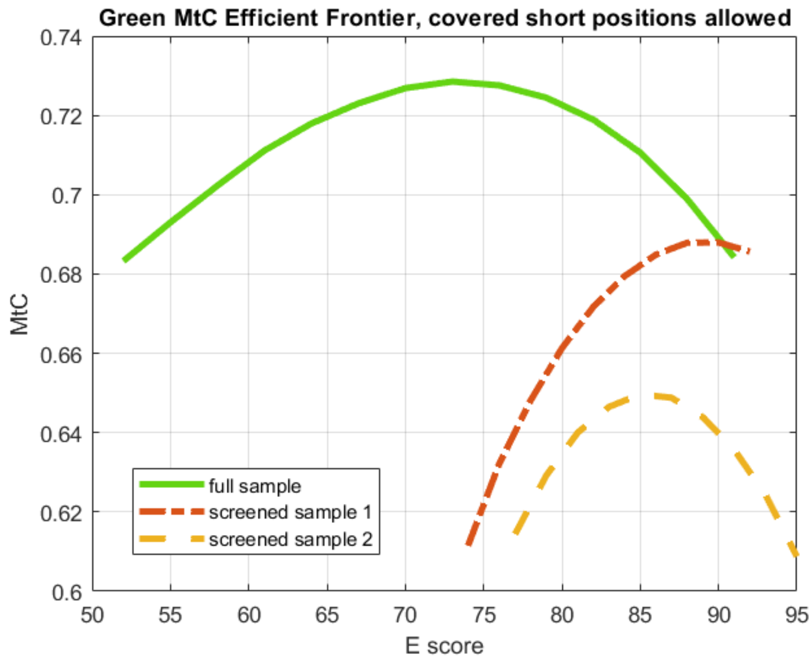

Figure 4: Green MtC efficient frontier for the complete STOXX Euro 100 dataset and for the exclusionary screening strategy, covered short positions allowed. Data from 2007-2019.

Allowing for short sales makes it possible to have better performing portfolios for all E scores and a less costly trade-off between economic and environmental performance, but at the cost of a real environmental impact more difficult to assess. If in the no short sale strategy raising the required E score translates to a direct increase in the proportion of wealth invested in the higher rated asset, in this case even for a higher E score portfolio some brown assets are still bought and some greener ones sold.

Table 2: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score using the complete STOXX Europe dataset, covered short positions allowed. Data from 2007-2019.

E Score	**Return**	**CVaR**
91	0.2668	0.3899
88	0.2767	0.3959
85	0.2827	0.3978
82	0.2890	0.4020
79	0.2943	0.4062
76	0.2974	0.4087
73	0.2992	0.4108
70	0.2962	0.4075
67	0.2967	0.4104
64	0.3011	0.4194
61	0.3014	0.4238
58	0.3058	0.4354
55	0.3102	0.4477
52	0.3155	0.4617

Table 3: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score using the STOXX Europe dataset after removing the stocks with E score lower than the 20th percentile, covered short positions allowed. Data from 2007-2019.

E Score	**Return**	**CVaR**
92	0.2848	0.4155
90	0.2823	0.4103
88	0.2773	0.4031
86	0.2745	0.4008
84	0.2770	0.4077
82	0.2766	0.4118
80	0.2746	0.4152
78	0.2731	0.4213
76	0.2760	0.4366
74	0.2768	0.4526

Observing the expected return and CVaR obtainable for each E score (Table 2), we can see the same pattern observed before. The consecutive pairs of CVaRs have been tested and the null has been always rejected at 99% level, proving how imposing higher E scores causes a statistically significant reduction of the CVaR.

On the contrary, for the screening strategy obtained by removing the stocks with E score lower than the 20th percentile, we find that portfolios with higher E scores have higher expected return and CVaR (Table 3); portfolios with lower E score are on the inefficient part of the frontier.

We empirically find the following pattern: increasing the E score required significantly reduces the CVaR of the portfolio. This is in accordance with the part of the literature stating that stocks performing better environmentally-wise grants lower expected return and lower risk with respect to their lower-rated counterparts (Zerbib 2022, Pedersen, Fitzgibbons, and Pomorski 2021, Bolton and Kacperczyk 2021, Pástor, Stambaugh, and Taylor 2021). This reduction happens until a certain threshold E score is reached; pushing the portfolio E score above it results in inefficient investment decisions, with higher CVaR and lower expected returns. Limiting the pool of assets or constraining the investor into not taking short positions lowers the threshold E score beyond which the portfolios become inefficient.

3.3 The MtC efficient frontier by sector

The frontier for each sector has been obtained by repeatedly maximizing the MtC ratio at the confidence level of $\alpha = 95\%$ allowing for short sales and imposing different levels of the E score.

To better illustrate differences and similarities among the sectors we present a more in-depth analysis comparing Financials, Basic Materials, and Energy

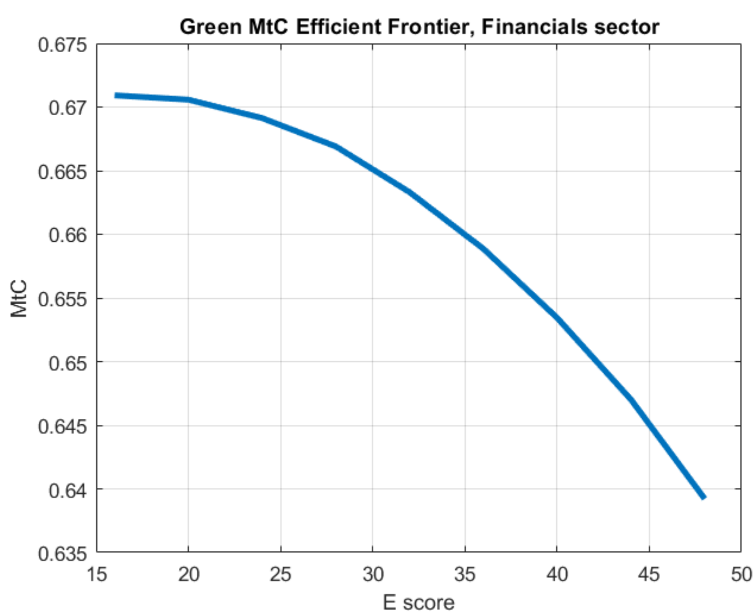

Figure 5: Green MtC efficient frontier for Financials, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

Table 4: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Financials, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

E Score	**Return**	**CVaR**
48	0.3233	0.5058
44	0.3246	0.5016
40	0.3230	0.4943
36	0.3263	0.4952
32	0.3283	0.4949
28	0.3275	0.4911
24	0.3352	0.5010
20	0.3377	0.5036
16	0.3443	0.5132
12	0.3488	0.5211
10	0.3513	0.5258

We start examining the Financials sector, which together with Consumer Discretionary and Industrials, is granting the highest MtC for all E scores studied. The maximum MtC portfolio is obtained for the very low E score of 16. Requiring an E score 4 points higher leads to a MtC $0,045\%$ smaller from 16 to 20, while from 44 to 48 the ratio is $1,206\%$ smaller (tested at 99% confidence interval): the loss of MtC is non-linear with the increase in the required E score.

Analyzing the pairs of expected return and CVaR in Table 4, we see the same pattern highlighted in the previous section: the CVaR decreases as the required E score increases up to a threshold E score, after which only inefficient portfolios are found. In this case, the E score beyond which the investment decisions become inefficient is significantly lower.

The frontier for the Basic Materials is presented in Figure 6. The frontier grants overall lower MtC, but the the highest ratio portfolio is obtained at a higher score; also in this case the performance loss increases with the score, reaching -1.13% when passing from 68 to 72. The behaviour of the expected returns and CVaR obtained for each portfolio is illustrated in Table 5 and it is in line with what was previously observed.

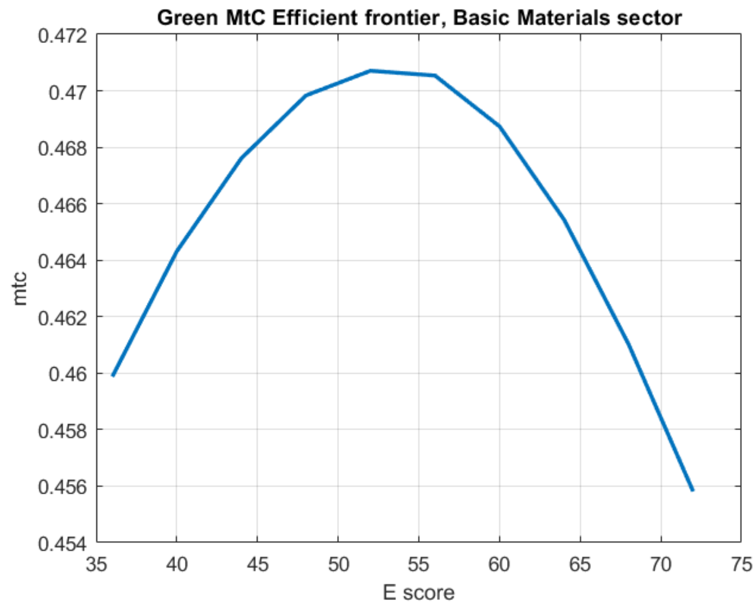

Figure 6: Green MtC efficient frontier for Basic Materials, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

Table 5: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Basic Materials, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

E Score	**Return**	**CVaR**
72	0.2488	0.5458
68	0.2515	0.5456
64	0.2528	0.5432
60	0.2526	0.5388
56	0.2554	0.5427
52	0.2566	0.5451
48	0.2584	0.5500
44	0.2612	0.5586
40	0.2633	0.5672
36	0.2621	0.5700

The last sector examined is Energy. The green MtC efficient frontier in Figure 7 is characterized by a sharp decline in MtC ratios with increasing values of the E score. The Energy sector shows a peculiar behaviour of the pair of expected return and CVaR: to higher E scores correspond to higher CVaR and expected return, and that the portfolios with lower E scores are inefficient, as can be seen in Table 6. These results suggest that the relationship between CVaR and E score could be sector-specific.

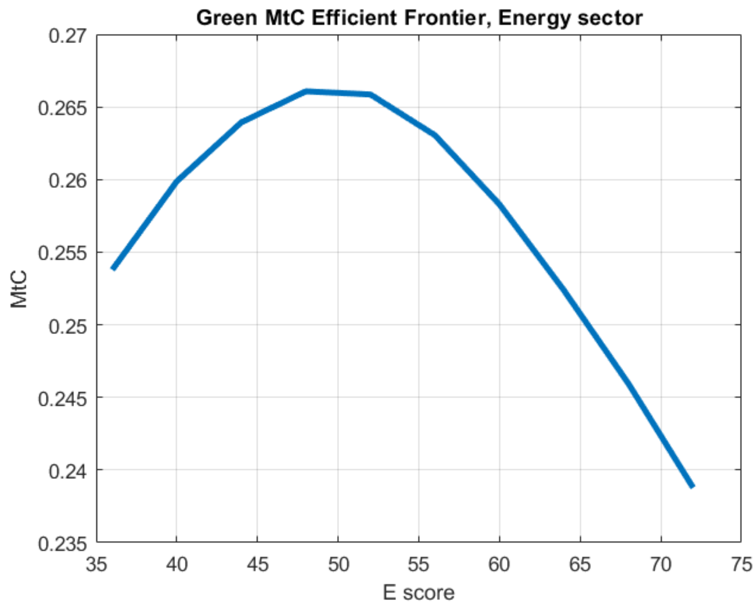

Figure 7: Green MtC efficient frontier for Energy, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

Table 6: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Energy, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

E Score	**Return**	**CVaR**
72	0.1963	0.8223
68	0.1948	0.7921
64	0.1934	0.7663
60	0.1908	0.7387
56	0.1890	0.7184
52	0.1871	0.7039
48	0.1853	0.6965
44	0.1829	0.6931
40	0.1812	0.6973
36	0.1791	0.7058

All the frontiers and the mean-CVaR pairs for each score for the remaining sectors are reported in Appendix.

4 Conclusions

In light of the recent increased interest in green investment strategies, in this work, we empirically investigated the performance of a portfolio built in a way to incorporate investors' environmental concerns.

The main features of the methodology used are the use of the MtC ratio and of the E scores to proxy investors' environmental preferences. The use in the MtC of the CVaR as a risk measure makes it better suited to capture tail events. By maximizing the MtC for different required E scores we obtain the efficient frontier, which can visually show the relationship between portfolio performance and E score. This analysis has been conducted using daily returns from the European market. We compared the results in the case of no short sales allowed and covered short positions, for the full dataset and for two screened samples; the analysis has been conducted as well for the different sectors in which stocks are classified.

We observed that in order to achieve a better E score investors need to accept worse-performing portfolios: an E score higher or lower than that of the market portfolio hinders the investment performance. This is true for all strategies studied. Furthermore, we showed that portfolios with higher E score have lower CVaR, up to a certain threshold, beyond which only inefficient allocations are found. Lastly, in our sectoral analysis, we found that in all sectors portfolios with higher E scores have lower CVaRs, with the exception of Energy.

These results might be helpful to responsible investors, who inevitably need to trade off part of the portfolio performance to have their E score requirements met. The strategy that grants a better trade-off is the MtC maximization allowing for short positions over the full sample, but that comes at the cost of an environmental impact more difficult to assess. Furthermore, some target E scores might not be reachable, since after that only inefficient portfolios are found.

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Frontiers by sectors

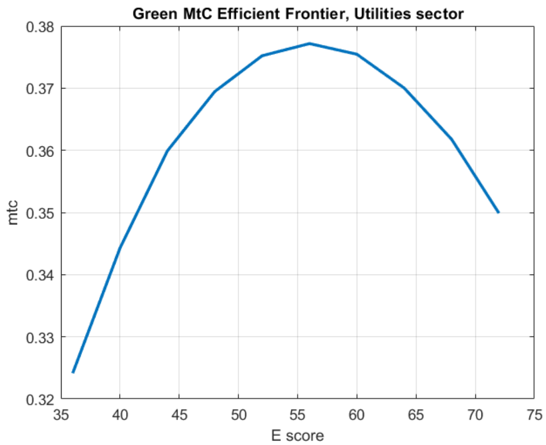

Figure 8: Green MtC efficient frontier for Utilities, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

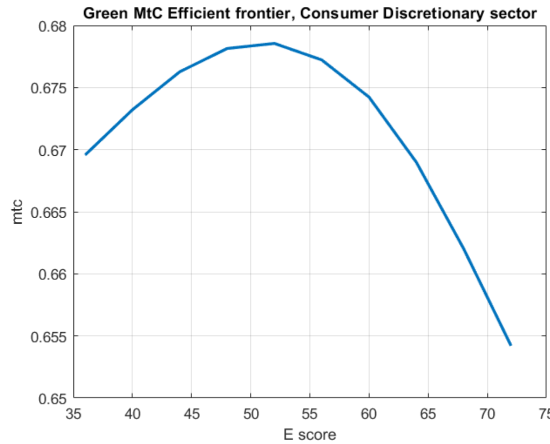

Figure 9: Green MtC efficient frontier for Consumer Discretionary, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

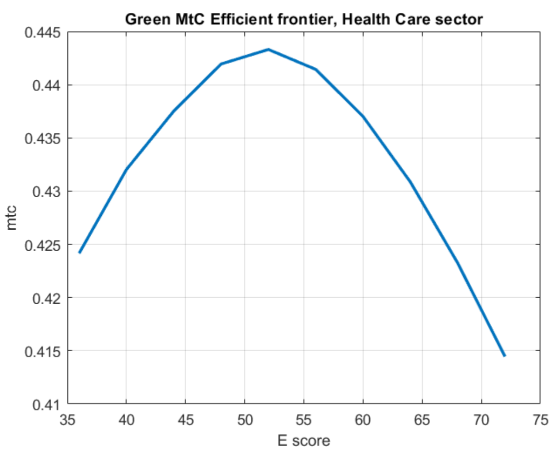

Figure 10: Green MtC efficient frontier for Health Care, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

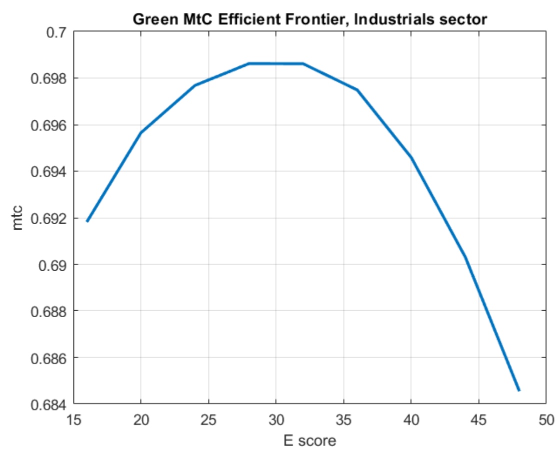

Figure 11: Green MtC efficient frontier for Industrials, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

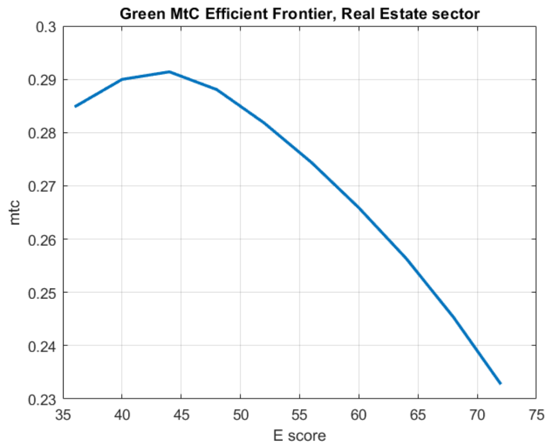

Figure 12: Green MtC efficient frontier for Real Estate, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

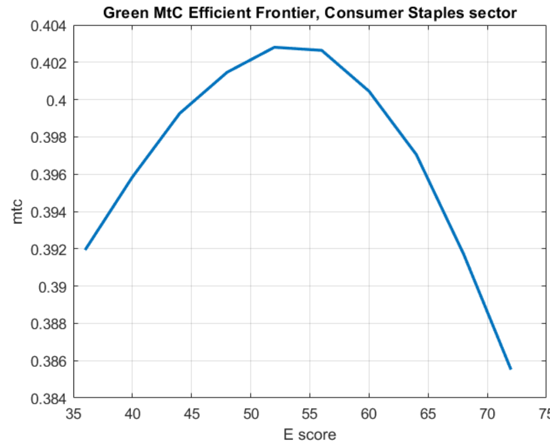

Figure 13: Green MtC efficient frontier for Consumer Staples, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

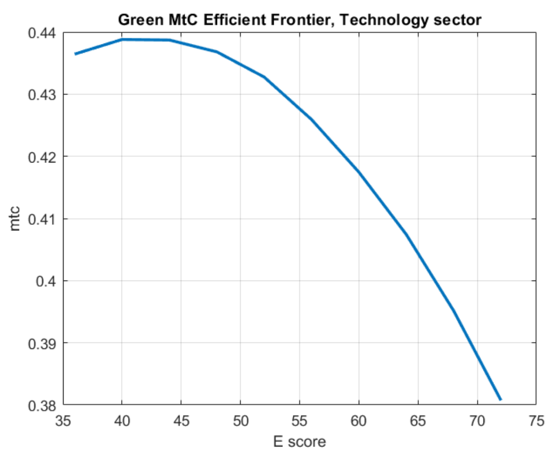

Figure 14: Green MtC efficient frontier for Technology, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

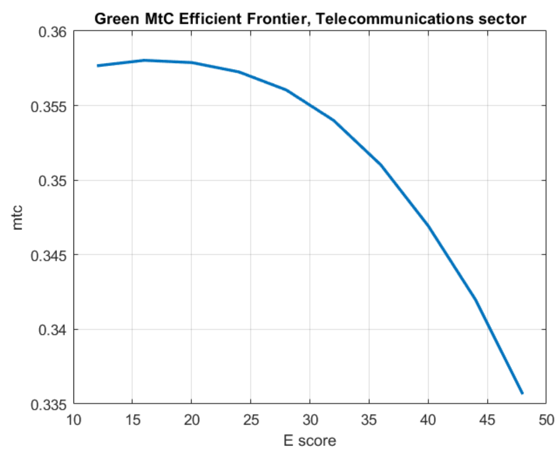

Figure 15: Green MtC efficient frontier for Telecommunications, covered short positions allowed. Data from STOXX Europe, for the years 2007-2019.

Annualized CVaR and expected return by sector

Table 7: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Utilities, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
72	0.1704	0.4871
68	0.1779	0.4918
64	0.1833	0.4954
60	0.1859	0.4952
56	0.1864	0.4942
52	0.1913	0.5100
48	0.1972	0.5339
44	0.2023	0.5622
40	0.2028	0.5891
36	0.1995	0.6156

Table 8: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Consumer Discretionary, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
72	0.3173	0.4851
68	0.3220	0.4865
64	0.3217	0.4808
60	0.3232	0.4794
56	0.3241	0.4785
52	0.3277	0.4830
48	0.3296	0.4861
44	0.3307	0.4890
40	0.3324	0.4937
36	0.3312	0.4947

Table 9: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Health Care, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
72	0.2209	0.5330
68	0.2223	0.5252
64	0.2249	0.5220
60	0.2266	0.5186
56	0.2250	0.5097
52	0.2260	0.5098
48	0.2270	0.5136
44	0.2305	0.5269
40	0.2290	0.5301
36	0.2307	0.5438

Table 10: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Industrials, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
48	0.3055	0.4463
44	0.3093	0.4480
40	0.3130	0.4506
36	0.3145	0.4508
32	0.3130	0.4481
28	0.3073	0.4399
24	0.3030	0.4343
20	0.3031	0.4357
16	0.3022	0.4368

Table 11: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Real Estate, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
72	0.2202	0.9461
68	0.2315	0.9438
64	0.2436	0.9503
60	0.2535	0.9536
56	0.2637	0.9610
52	0.2703	0.9590
48	0.2847	0.9884
44	0.3036	1.0420
40	0.3163	1.0909
36	0.3228	1.1333

Table 12: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Consumer Staples, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
72	0.1937	0.5024
68	0.1940	0.4953
64	0.1958	0.4932
60	0.1996	0.4985
56	0.1988	0.4938
52	0.1964	0.4877
48	0.1937	0.4824
44	0.1900	0.4760
40	0.1897	0.4793
36	0.1897	0.4841

Table 13: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Technology, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
72	0.2933	0.7703
68	0.3035	0.7681
64	0.3117	0.7651
60	0.3231	0.7739
56	0.3308	0.7767
52	0.3372	0.7792
48	0.3423	0.7835
44	0.3526	0.8037
40	0.3588	0.8178
36	0.3505	0.8030

Table 14: Yearly return and CVaR of the maximum MtC portfolio obtained for each E score for Telecommunications, covered short positions allowed. Data from STOXX Europe for the years 2007-2019.

Score	**Return**	**CVaR**
48	0.1657	0.5985
44	0.1701	0.5897
40	0.1756	0.5862
36	0.1819	0.5871
32	0.1854	0.5805
28	0.1899	0.5792
24	0.1937	0.5770
20	0.2021	0.5911
16	0.2106	0.6072
12	0.2212	0.6303