ESG: A New Dimension in Portfolio Allocation

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Abstract

In this paper, we examine the impact of including environmental, social and governance (ESG) criteria in the allocation of equity portfolios. We focus on the risk and return characteristics of the resulting ESG portfolios and investment strategies. Two specific measures are considered to quantify the ESG performance of a company; the ESG rating and the greenhouse gas (GHG) emission intensity. For both measures, we carry out empirical portfolio analyses with assets in either the STOXX Europe 600 or the Russell 1000 index. The ESG rating data analysis does not provide clear-cut evidence for enhanced performance of portfolios with either high or low ESG scores. We moreover illustrate that the choice of rating agency has a significant impact on the performance of the resulting ESG-constrained portfolios. Secondly, we study the impact of GHG emission reductions and increases. We show that emission reductions do not necessarily lead to increased risk or diminished returns, which gives confidence in a smooth transition towards the green economy pursued by the European Green Deal.

1 Introduction

Sustainable investing, socially responsible investing, impact investing or ESG investing: the extensive terminology alone shows that a lot of market participants aim to achieve a rather common goal that we call for simplicity "green investing". All of the above mentioned investing styles do have their rather individual specifics. However, they all consider environmental, social and governance (ESG) topics at their core and aim to improve companies and/or portfolios along these dimensions for all stakeholders. While a long term positive impact on companies emphasizing ESG performance is rarely disputed, one question remains and is heavily debated: 'What is the impact of green investing on risk and return?'. This is the exact topic we want to address in this study.

There are many ways in which investors try to 'go green'. The humble beginnings of green investing are rooted in simple exclusions of companies with poor E, S or G practices. There is quite a debate regarding the effectiveness of this approach towards actual change in the behavior of companies and the overall market. Proponents of the exclusion approach argue that it has a direct impact on a company's cost of capital and is hence an effective tool to support change in the overall market ([1]). Opponents of the approach however point to the very nature of stock markets and argue that excluding a certain stock only transfers ownership from an unwilling investor to a more willing one ([3]). To ensure full comparability with standard benchmarks we do not use exclusions

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in this study, thus avoiding this discussion and leaving it to further debate. Instead, we focus on a purely data-driven approach. With specific ESG data sets becoming more readily available, the market saw the advent of what is commonly known as best-in-class approaches. These methods evaluate stocks according to different metrics in order to identify leaders and laggards in the respective criteria. Our analysis aims for a broad view that is generally applicable. We construct portfolios along the mean-variance efficient frontier with different constraints regarding the ESG performance of its constituents. As mentioned before, all stocks in the investment universe can be included in this type of portfolio construction. Restrictions thus only stem from ESG constraints on the portfolio as a whole. We find this to be a very practical approach as in our view most investors will eventually construct portfolios with similar constraints to their respective utility functions.

In this paper, we consider two particular measures to quantify sustainability; the ESG score as a broad factor capturing a company's overall ESG performance, and the greenhouse gas intensity as a climate change related factor. We consider the impact of including both measures in a mean-variance allocation framework and analyze how the efficient frontier shifts and behaves when varying degrees of greenness are enforced. When considering ESG scores, we enter the research domain that explores the relation between a company's general ESG performance and its financial performance. The majority of studies in the literature find a positive relation between ESG performance and corporate financial performance, see e.g. [10] for a review study. In this paper, we contribute by approaching the problem from the perspective of portfolio allocation. We do not only focus on the long term performance, but also consider the additional price of risk to be paid for holding a green portfolio. On the other hand, the study on greenhouse gas intensities gives some insights into the impact of the European Green Deal [9] on equity portfolios, as the initiatives therein heavily focus on reducing greenhouse gas emissions. We adopt the greenhouse gas reduction targets as proposed in the TEG report on climate benchmarks [7] and measure the risk and return of both low and high emission portfolios.

The remainder of the paper is organized as follows. In Section 2, we set the notation for the allocation framework and explain how ESG criteria are included. Section 3 is dedicated to an empirical portfolio analysis including ESG rating data. We analyze portfolios in both European and American equity markets, represented by the STOXX Europe 600 and Russell 1000 index respectively. In Section 4, we focus on greenhouse gas intensities and aim to measure the impact of either emission reductions or increases on the performance and risk behavior of portfolios in the European and American market. Section 5 concludes the paper.

2 The allocation framework

In this paper, standard mean-variance portfolio allocation [12] will serve as the benchmark allocation framework. Therefore, consider N risky assets with dividend-adjusted return on the ith asset given by a random variable R_i with mean μ_i. Define

$$\boldsymbol{R} = (R_1, \ldots, R_N)^t, \tag{1}$$

$$\boldsymbol{\mu} = \mathbb{E}[\boldsymbol{R}] \tag{2}$$

and let $\boldsymbol{\Sigma}$ be the covariance matrix of $\boldsymbol{R}$. Let

$$\boldsymbol{w} = (w_1, \ldots, w_N)^t \tag{3}$$

be a vector of non-negative portfolio weights satisfying $\sum_{i=1}^{N} w_i = 1$. Hence, we do not allow for short selling. In this setting, one allocates the investment portfolio by minimizing its riskiness for a desired level of expected return (μ_P). Measuring the risk traditionally by the volatility of the portfolio, this boils down to solving the following quadratic program:

$$\begin{aligned} \underset{\boldsymbol{w} \geq \mathbf{0}}{\text{minimize}} \quad & \boldsymbol{w}^t \boldsymbol{\Sigma} \boldsymbol{w} \\ \text{subject to} \quad & \boldsymbol{\mu}^t \boldsymbol{w} = \mu_P \\ & \mathbf{1}^t \boldsymbol{w} = 1. \end{aligned} \tag{4}$$

Portfolios are hence allocated along two dimensions: expected return and volatility. In this paper, we include a third dimension consisting of environmental, social and governance (ESG) criteria that characterize the sustainability of a portfolio. Therefore, denote γ_i for a particular sustainability indicator of the ith asset. This could be, for instance, a generic ESG rating of the related company, or it could be a more specific metric like the greenhouse gas emissions intensity, employee turnover rate, gender pay equality, etc.

There are various ways to impose ESG requirements on the portfolio. We discuss three methods in particular, based on the mean-variance framework in (4).

Constrained mean-variance portfolios

An overall portfolio ESG constraint γ_P is imposed by optimizing the quadratic program

$$\begin{aligned} \underset{\boldsymbol{w} \geq \mathbf{0}}{\text{minimize}} \quad & \boldsymbol{w}^t \boldsymbol{\Sigma} \boldsymbol{w} \\ \text{subject to} \quad & \mathbf{1}^t \boldsymbol{w} = 1 \\ & \boldsymbol{\mu}^t \boldsymbol{w} = \mu_P \\ & \boldsymbol{\gamma}^t \boldsymbol{w} \leq \gamma_P \end{aligned} \tag{5}$$

where $\boldsymbol{\gamma} = (\gamma_1, \dots, \gamma_N)^t$ consists of the sustainability indicators of the portfolio constituents. Solving this problem for different target returns leads to a restricted efficient frontier, which is by construction less optimal (in mean-variance sense) than the benchmark frontier.

Green-variance portfolios

Alternatively, one can leave aside the expected returns and replace the target return in (4) by a sustainability target, i.e.

$$\begin{aligned} \underset{\boldsymbol{w} \geq \mathbf{0}}{\text{minimize}} \quad & \boldsymbol{w}^t \boldsymbol{\Sigma} \boldsymbol{w} \\ \text{subject to} \quad & \mathbf{1}^t \boldsymbol{w} = 1 \\ & \boldsymbol{\gamma}^t \boldsymbol{w} = \gamma_P. \end{aligned} \tag{6}$$

For instance, this allows to fix a target level of greenhouse gas emissions and allocate the portfolio towards a minimum risk level for which the target is reached. Note that these portfolios do not necessarily yield a competitive return. In order to account for this, one could add a lower bound for the expected portfolio return

$$\boldsymbol{\mu}^t \boldsymbol{w} \geq \mu_P \tag{7}$$

to the optimization problem (6).

Most similar constrained portfolios

A third approach consist in optimizing for the sustainable portfolio that is as similar as possible to the mean-variance portfolio, defined as the solution $\boldsymbol{w}_{\mathrm{MV}}$ of (4). When measuring similarity by the squared difference in portfolio weights, we find the optimal portfolio as follows:

$$\begin{aligned} \underset{\boldsymbol{w}\geq\boldsymbol{0}}{\text{minimize}} \quad & (\boldsymbol{w}-\boldsymbol{w}_{\mathrm{MV}})^t\,(\boldsymbol{w}-\boldsymbol{w}_{\mathrm{MV}}) \\ \text{subject to} \quad & \boldsymbol{1}^t\boldsymbol{w}=1 \\ & \boldsymbol{\gamma}^t\boldsymbol{w}\leq\gamma_P. \end{aligned} \tag{8}$$

An advantage of the latter formulation is that it yields a portfolio that can be obtained by reallocating the mean-variance portfolio as little as possible in order to make it comply with sustainability requirements. Note that this approach works for any kind of reference portfolio, especially for index tracking with ESG constraints.

In the three approaches outlined above, an overall ESG constraint is imposed on the portfolio rather than on the individual assets. Hence, we do not focus on portfolios that exclude particular assets because of their ESG indicator values. The remainder of the paper consists of an empirical analysis of the impact of including two sustainability indicators in particular. The first application is based on ESG ratings, which attempt to score a company on their overall environmental, social and governance practices. In the second application, we focus on the environmental aspect and evaluate companies on their greenhouse gas emissions intensity.

3 ESG ratings as sustainability indicator

In this section, we quantify the sustainability of a company by its ESG rating issued by MSCI ESG Research. MSCI computes a rating, or score, based on raw scores and weights of 37 ESG key issues across the three E, S and G pillars. Raw scores take into account both a company's exposure to key issues and their management. To obtain a good score on a key issue, a company with high exposure should provide strong management, whereas a company with limited exposure can have a more modest managing approach. An industry-specific weight is assigned to each indicator in order to assess its importance for the companies in that sector. Raw scores and weights are combined into the weighted average key issue score, i.e.

$$\text{ESG score} = \sum_{i=1}^{37} \text{raw score}_i \cdot \text{weight}_i \tag{9}$$

which is an overall company sustainability grade between 0 (very poor) and 10 (very good). Note that this score is not normalized by industry, in contrast to the widely reported MSCI ESG Letter Ratings. The ESG data set used in our analysis is updated quarterly, with reporting dates in March, June, September and December.

In the analysis that follows, we include ESG ratings into the allocation of equity portfolios in two different market universes; a European and an American universe. For both universes, we empirically analyze the impact of including ESG constraints by means of the ESG scores defined in Equation (9). As criticized in the literature, e.g. [2], [6], [4], ESG ratings from different rating agencies do not always agree, and the results might differ when ratings from another provider were used. In the last part of this section, we briefly touch upon this concern with a discussion based on ESG ratings issued by Sustainalytics.

3.1 The European market: STOXX 600

We inspect the impact of ESG constraints in the European stock market, represented by the assets in the STOXX Europe 600 index[1]. First, we construct the efficient frontier and illustrate how it is shifted when ESG requirements are introduced. In Subsection 3.1.2, we define related ESG investment strategies and evaluate how they performed over a ten-year period from December 2009 until December 2019. All strategies are compared in terms of return, risk and concentration measures.

3.1.1 The efficient frontier

We first construct the mean-variance efficient frontier without taking into account ESG information. Expected returns and covariances are estimated on time series of historical daily returns[2], covering a two-year period from 10 September 2017 until 10 September 2019. The investment universe is restricted to the 552 assets for which there is both historical return data and current ESG rating data at our disposal. The corresponding minimum variance portfolio and the efficient frontier are represented by respectively the black bullet and the black line in Figure 1.

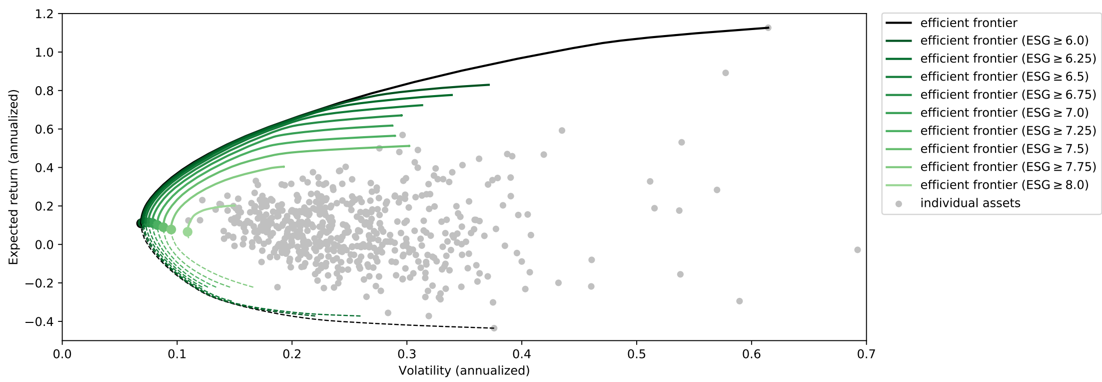


Figure 1: Mean-variance efficient STOXX 600 portfolios subject to positive ESG rating constraints.

A calculation of the ESG scores - after allocating the portfolios - results in a score of 5.53 for the minimum variance portfolio. Other portfolios on the efficient frontier have an ESG score between 5.53 and 5.74, as long as the expected return of the portfolio is below 75% per annum. Portfolios with higher expected returns have lower ESG scores. Figure 1 also depicts green efficient frontiers, resulting from optimization problem (5) with ESG constraints

$$\mathbf{ESG}^t \boldsymbol{w} \geq \gamma_P \qquad \gamma_P = 6,\, 6.25,\, \ldots,\, 8, \tag{10}$$

where

$$\mathbf{ESG} = (\mathrm{ESG}_1, \ldots, \mathrm{ESG}_{552})^t \tag{11}$$

are the ESG scores of the assets reported on 10 September 2019. The ESG criteria included in the allocation procedure are hence only evaluated for the ratings published on the allocation date, without taking into account former rating information.

[1] The investment universe includes the STOXX 600 constituents as of March 2020. We do not see survivorship bias as a problem, as we only compare within the same data set.

[2] Returns are based on dividend-adjusted closing prices (in EUR).

Figure 1 shows that a modest rise in the portfolio ESG score not necessarily has a large impact on the efficient frontier. Only when the required ESG score is set higher than 7, the frontier substantially drops. We further observe that the expected returns of the green minimum variance (GMV) portfolios, represented by the green bullets, slightly increase for soft ESG constraints and decrease when the constraints become stronger.

In a similar fashion, we can impose brown ESG constraints on the portfolio if we require the portfolio ESG score to be below a preset target value, i.e.

$$\mathbf{ESG}^t \boldsymbol{w} \leq \gamma_P \qquad \gamma_P = 2.5,\, 2.75,\, \ldots,\, 5. \tag{12}$$

Solving problem (5) with these adverse ESG constraints results in the brown efficient frontiers in Figure 2.

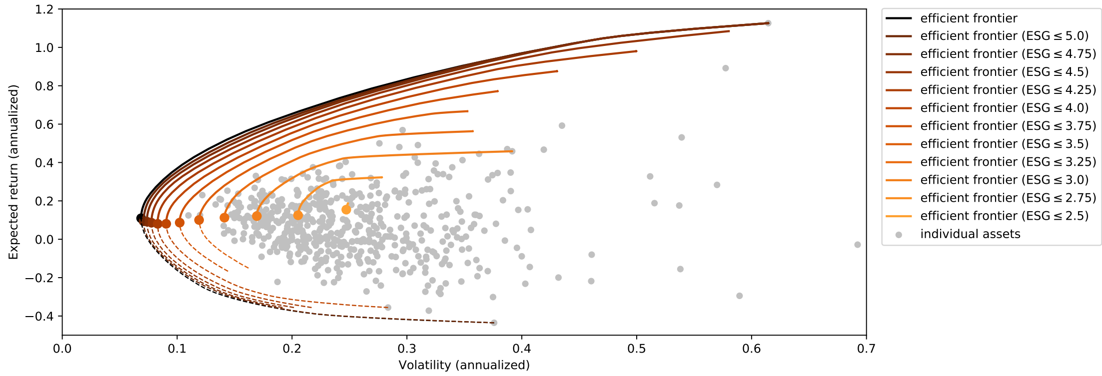


Figure 2: Mean-variance efficient STOXX 600 portfolios subject to negative ESG rating constraints.

In this case, the expected return of the brown minimum variance (BMV) portfolio, represented by the brown bullets, slightly decreases for soft ESG constraints and then increases when the constraints become stronger. The opposite effect was observed for green ESG constraints in Figure 1. This can also be seen in Table 1, where the expected returns (μ_{GMV}, μ_{BMV}) and volatilities (σ_{GMV}, σ_{BMV}) of the minimum variance portfolios are explicitly listed for all green and brown constraints. The first row in Table 1 states the properties of the minimum variance portfolio without ESG constraints.

constraint	$\boldsymbol{\sigma}_{\mathbf{GMV}}$	$\boldsymbol{\mu}_{\mathbf{GMV}}$	**ENC**	**constraint**	$\boldsymbol{\sigma}_{\mathbf{BMV}}$	$\boldsymbol{\mu}_{\mathbf{BMV}}$	**ENC**
–	6.86%	10.95%	17.36	–	6.86%	10.95%	17.36
ESG $\geq$ 6	6.97%	11.30%	17.06	ESG $\leq$ 5	7.08%	9.40%	21.22
ESG $\geq$ 6.25	7.09%	11.40%	15.81	ESG $\leq$ 4.75	7.37%	9.18%	21.64
ESG $\geq$ 6.5	7.27%	11.52%	14.75	ESG $\leq$ 4.5	7.76%	8.63%	18.85
ESG $\geq$ 6.75	7.53%	11.48%	13.91	ESG $\leq$ 4.25	8.31%	8.04%	14.41
ESG $\geq$ 7	7.85%	11.13%	13.23	ESG $\leq$ 4	9.05%	8.06%	10.97
ESG $\geq$ 7.25	8.28%	10.07%	12.66	ESG $\leq$ 3.75	10.22%	8.67%	8.32
ESG $\geq$ 7.5	8.80%	8.94%	11.31	ESG $\leq$ 3.5	11.91%	10.03%	6.26
ESG $\geq$ 7.75	9.48%	7.76%	8.91	ESG $\leq$ 3.25	14.12%	11.25%	4.58
ESG $\geq$ 8	10.91%	6.54%	5.40	ESG $\leq$ 3	16.94%	12.07%	3.16
				ESG $\leq$ 2.75	20.53%	12.51%	2.07
				ESG $\leq$ 2.5	%	%	1.31

Table 1: Properties of minimum variance STOXX 600 portfolios with various constraints on the ESG score.

The concentration of a portfolio $\boldsymbol{w}$ is measured by the effective number of constituents (ENC), see for instance [5], which is defined as the inverse of the Herfindahl-Hirschman index, i.e.

$$\mathrm{ENC}(\boldsymbol{w}) = \left(\sum_{i=1}^{552} w_i^2\right)^{-1}. \tag{13}$$

The least concentrated (equally-weighted) portfolio attains the maximum ENC of 552. Similarly, allocating all the money to only one of the 552 assets results in an ENC of 1. Lower values of the ENC hence correspond to more concentrated portfolios. Table 1 indicates that minimum variance portfolios tend to become more concentrated when stronger ESG constraints are imposed, suggesting a trade-off between sustainability and diversification of the portfolio. However, note that the ENC is purely a measure of concentration, which only naively quantifies diversification. For further details on the impact of ESG criteria on portfolio diversification, we refer to [11].

Let us now take a different point of view and search for the most sustainable portfolio for a given risk budget, without taking into account the expected return. Solving (6) with sustainability constraints

$$\mathbf{ESG}^t\boldsymbol{w} = \gamma_P \qquad \text{for } \gamma_P \in \big[\mathrm{ESG}_{\mathrm{MV}},\ \max\{\mathbf{ESG}\}\big], \tag{14}$$

where $\mathrm{ESG}_{\mathrm{MV}}$ is the ESG score of the minimum variance portfolio, gives the green frontier of the STOXX 600 universe depicted in Figure 3. This line can be interpreted as the minimum portfolio volatility required to satisfy a particular ESG target. The green frontier in Figure 3 shows that lifting the ESG score of the minimum variance portfolio does not require too much additional volatility. For instance, shifting the target ESG

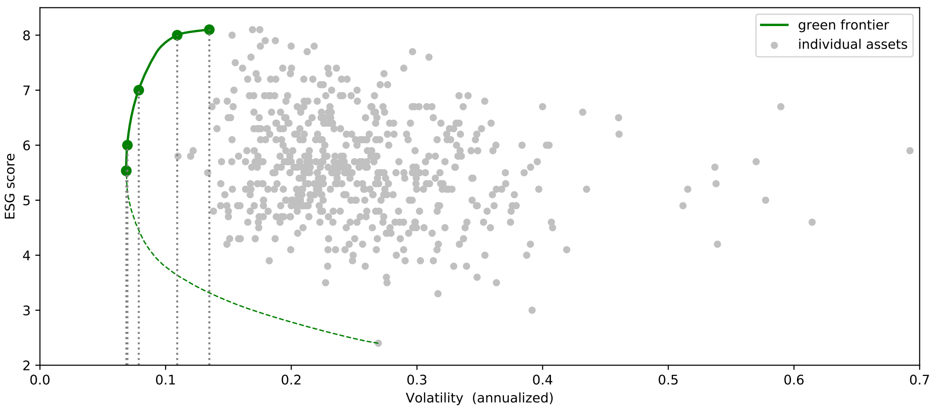


Figure 3: Green frontier of the STOXX 600 universe on 10 September 2019.

score of the portfolio from 5.53 to 6 increases the volatility with only 9 basis points. More details about the expected return (μ_{GV}), volatility (σ_{GV}) and concentration can be found in Table 2. It turns out that both expected returns and volatilities do not change a lot when the ESG score is at or below 7, while higher ESG targets result in both a lower expected return and a higher volatility. The ENC values of the selected green minimum variance portfolios indicate that the portfolios immediately become more concentrated when stronger ESG targets are enforced.

Finally, we search for the green STOXX 600 portfolio that is as similar as possible to the reference minimum variance portfolio. Solving problem (8) for several ESG targets

$$\mathbf{ESG}^t\boldsymbol{w} \geq \gamma_P \qquad \gamma_P = 6,\, 6.5,\, \ldots,\, 8, \tag{15}$$

ESG	$\sigma_{\mathbf{GV}}$	$\mu_{\mathbf{GV}}$	**ENC**
5.53	6.86%	10.95%	17.36
6	6.96%	11.31%	16.85
6.5	7.26%	11.51%	14.65
7	7.86%	11.13%	13.36
7.5	8.81%	8.90%	11.32
8	10.92%	6.58%	5.36
8.10	13.48%	7.25%	2.00

Table 2: Properties of STOXX 600 portfolios on the green frontier.

results in green portfolios with expected return and volatility as visualized by the green bullets in Figure 4. Similarly as in Figure 1, the expected return of portfolios with modest ESG constraints is higher than the return of the minimum variance portfolio, but reduces when the required ESG rating exceeds 7. More generally, one can optimize for the ESG compliant portfolio that is as close as possible to any other portfolio on the efficient frontier. This leads to the shifted frontiers in Figure 4.

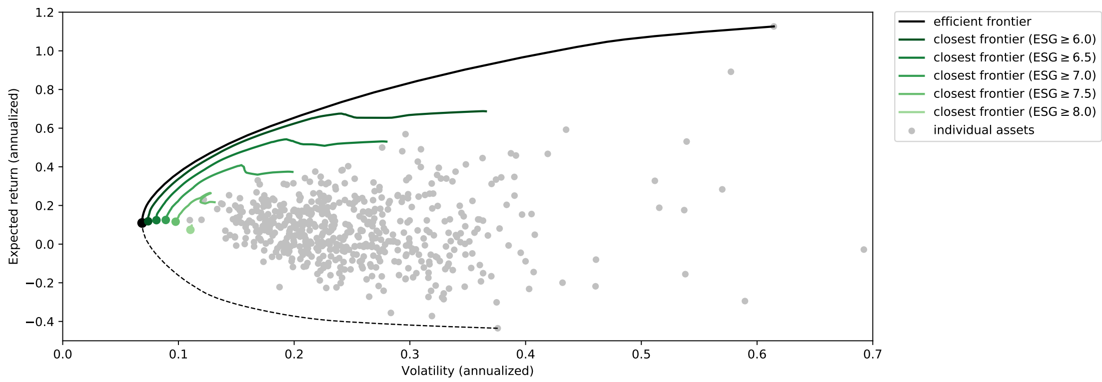


Figure 4: Green STOXX 600 portfolios that are most similar to those on the efficient frontier.

The frontiers obtained by this method are similar to the restricted frontiers in Figure 1, however, these frontiers are clearly less smooth and by construction less efficient in mean-variance sense. Table 3 presents the characteristics of green portfolios that are most similar to the minimum variance portfolio. Comparing these properties with those

constraint	$\sigma_{\mathbf{ms\text{-}G}}$	$\mu_{\mathbf{ms\text{-}G}}$	**ENC**
ESG ≥ 6	7.39%	11.82%	19.79
ESG ≥ 6.5	8.10%	12.40%	22.19
ESG ≥ 7	8.90%	12.50%	23.83
ESG ≥ 7.5	9.76%	11.59%	22.88
ESG ≥ 8	11.03%	7.40%	5.74

Table 3: Properties of the minimum variance STOXX 600 portfolios on the most similar green efficient frontier.

in Table 1 indeed reveals that the volatility of the most similar green portfolio ($\sigma_{\text{ms-G}}$) is generally higher than that of the green constrained portfolio (σ_{GMV}), for the same ESG requirements. On the other hand, higher ENC values indicate that these portfolios are less concentrated compared to the constrained minimum variance portfolios in Table 1.

3.1.2 ESG investment strategies

We define a set of ESG investment strategies based on the green allocation methods described in the previous section. Two types of strategies are distinguished:

1. **Minimum variance strategy**: invest in the minimum variance portfolio satisfying particular ESG constraints, i.e. solve (5).
2. **Highest similarity strategy**: invest in the ESG compliant portfolio with allocation (i.e weight distribution) that is most similar to the allocation of the classical minimum variance portfolio, i.e. solve (8).

Both strategies are executed for a period of approximately ten years, starting in December 2009. Portfolios are rebalanced quarterly, based on a two-year historical window of daily asset returns. The investment universe consists of those assets in the STOXX 600 index as of March 2020, for which there is both return data and ESG information available on the rebalancing date. Hence, the number of assets to invest in is not constant throughout the investment period, as can be seen in Figure 5. Indeed, the red line shows that the universe initially consists of 336 assets which steadily expands up to 552 assets in September 2019. Note that we do not see this as a problem, since we do not compare against the STOXX 600 index itself, but rather compare all strategies based on the same data set.

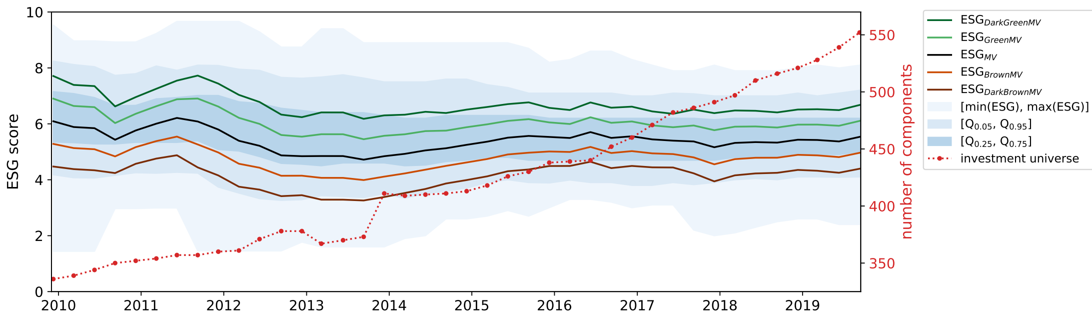


Figure 5: Left axis: portfolio ESG scores corresponding to the minimum variance STOXX 600 allocation strategies. Right axis: number of portfolio constituents.

In order to make the sustainability requirements proportionate over time, we define the constraints in function of the ESG performance of the standard minimum variance portfolio. In particular, we classify the sustainability, or greenness, of a portfolio $\boldsymbol{w}$ as follows,

$$\begin{aligned}
&\text{Dark green:} && \mathbf{ESG}^t\boldsymbol{w} \geq \mathrm{ESG}_{\mathrm{MV}} + 0.2\cdot(\max\{\mathbf{ESG}\} - \min\{\mathbf{ESG}\})\\
&\text{Green:} && \mathbf{ESG}^t\boldsymbol{w} \geq \mathrm{ESG}_{\mathrm{MV}} + 0.1\cdot(\max\{\mathbf{ESG}\} - \min\{\mathbf{ESG}\})\\
&\text{Brown:} && \mathbf{ESG}^t\boldsymbol{w} \leq \mathrm{ESG}_{\mathrm{MV}} - 0.1\cdot(\max\{\mathbf{ESG}\} - \min\{\mathbf{ESG}\})\\
&\text{Dark brown:} && \mathbf{ESG}^t\boldsymbol{w} \leq \mathrm{ESG}_{\mathrm{MV}} - 0.2\cdot(\max\{\mathbf{ESG}\} - \min\{\mathbf{ESG}\})
\end{aligned} \tag{16}$$

where $\mathrm{ESG}_{\mathrm{MV}}$ denotes the ESG score of the minimum variance portfolio on the rebalancing day. The black line in Figure 5 depicts this baseline ESG score throughout the entire investment period. The greenness of a strategy is thus defined by time-dependent

ESG constraints, relative to both the ESG score of the minimum variance portfolio and the variability of the ESG scores in the universe. The blue areas in Figure 5 give a coarse representation of the distribution of ESG scores in the investment universe on each allocation date. It can be seen that the distribution narrows over time, despite the fact that more companies are being included.

Let us now have a look at the out-of-sample performance of both strategies, each of them being executed according to the ESG constraints in (16). Figure 6 shows their daily historical performance, as well as the performance of the equally-weighted allocation strategy. The black line represents the minimum variance strategy, without incorporating ESG requirements. We observe that the green and dark green strategies yield a fairly similar return compared to the black minimum variance strategy. Portfolios can hence be made greener without altering their performance too much. On the other hand, (strong) brown ESG requirements lead to higher returns. However, it should be noted that the cumulative portfolio returns in Figure 6 do not take into account the riskiness of the strategies.

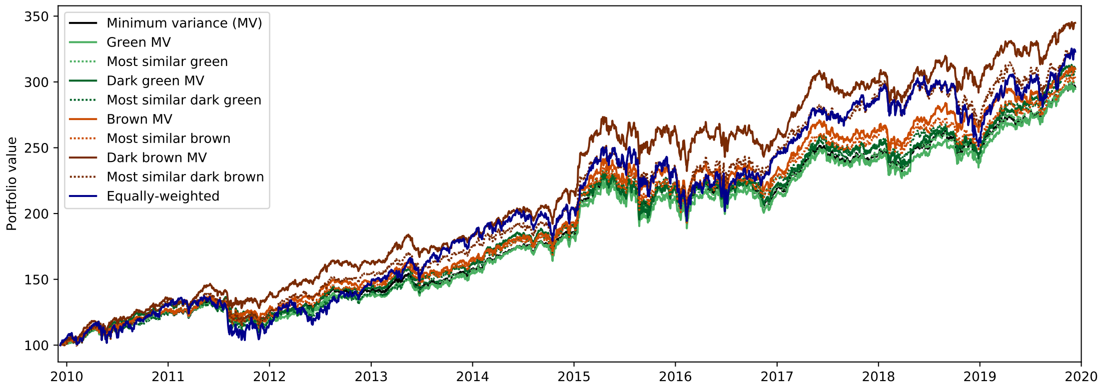


Figure 6: Historical performance of various STOXX 600 allocation strategies.

Table 4 evaluates the strategies based on a couple of performance and risk measures. The first measure is the overall (ten-year) maximum drawdown (MDD), i.e.

$$\text{MDD} = \min\left\{ \frac{value_i}{\max\{value_j |\ j = 1, \ldots, i\}} \,\middle|\, i = 1, \ldots, n_{days} \right\} - 1 \tag{17}$$

with n_{days} the number of working days throughout the 10-year investment period, r_j the return of a strategy on the jth working day, and $value_i$ the cumulative return up to the ith working day, i.e.

$$value_i = \prod_{j=1}^{i} (1 + r_j). \tag{18}$$

The MDD of the dark brown minimum variance strategy (DBMV) is the least severe, with a drop of only 15.04%. The brown and dark green minimum variance strategy are the only other strategies that have a better MDD value than the minimum variance reference strategy. The highest similarity strategies, indicated by the prefix 'ms', incur larger drawdowns - only the equally-weighted strategy performs worse.

The annualized rate of return in Table 4 translates the cumulative returns in Figure 6 to a yearly rate, i.e.

$$\text{annualized return} = \left(\prod_{i=1}^{n_{days}} (1 + r_i) \right)^{1/10}. \tag{19}$$

	MV	GMV	ms-G	DGMV	ms-DG	BMV	ms-B	DBMV	ms-DB	EW
MDD	-16.29%	-16.35%	-17.24%	-15.95%	-17.75%	-15.57%	-18.16%	-15.04%	-20.37%	-24.39%
Annualized return	11.47%	11.41%	11.54%	11.98%	11.85%	11.97%	11.72%	13.18%	12.40%	12.44%
Annualized volatility	10.63%	10.75%	11.38%	11.00%	12.43%	10.74%	11.48%	11.34%	12.92%	16.44%
Sortino ratio	1.56	1.54	1.57	1.61	1.67	1.47	1.39	1.48	1.39	1.13
1-day $\text{VaR}_{0.95}$	-0.95%	-0.99%	-1.03%	-1.05%	-1.16%	-0.99%	-1.04%	-1.08%	-1.23%	-1.60%
1-day $\text{VaR}_{0.99}$	-1.80%	-1.82%	-1.89%	-1.83%	-2.08%	-1.75%	-1.91%	-1.86%	-2.21%	-2.88%

Table 4: Risk and performance statistics of all STOXX 600 strategies based on the entire investment period (December 2009 - December 2019).

Both dark brown strategies and the equally-weighted strategy yield an annualized return above 12%, while all other strategies end up between 11.41% and 11.98%. The reported volatility is computed as the annualized standard deviation of the daily log-returns:

$$\text{annualized volatility} = \text{SD}(\log(1+\boldsymbol{r})) \cdot \sqrt{n_{days}/10}\,. \tag{20}$$

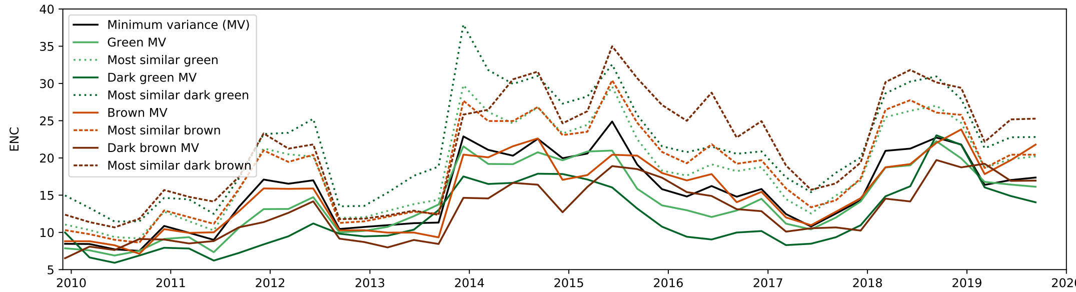
The minimum variance reference strategy has the lowest realized volatility of 10.63% per annum. Highest similarity strategies again turn out to be more risky, each having a volatility between 11% and 13%. All constrained minimum variance strategies, except for the dark brown version, have a volatility at or below 11%, exceeding the volatility of the minimum variance strategy with at most 37 basis points. The (annualized) Sortino ratio, defined as

$$\text{Sortino ratio} = \frac{\frac{1}{n_{days}}\sum_{i=1}^{n_{days}} r_i}{\sqrt{\frac{1}{n_{days}}\sum_{i=1}^{n_{days}} r_i^2\ \mathbf{1}_{\{r_i<0\}}}} \cdot \sqrt{n_{days}/10} \tag{21}$$

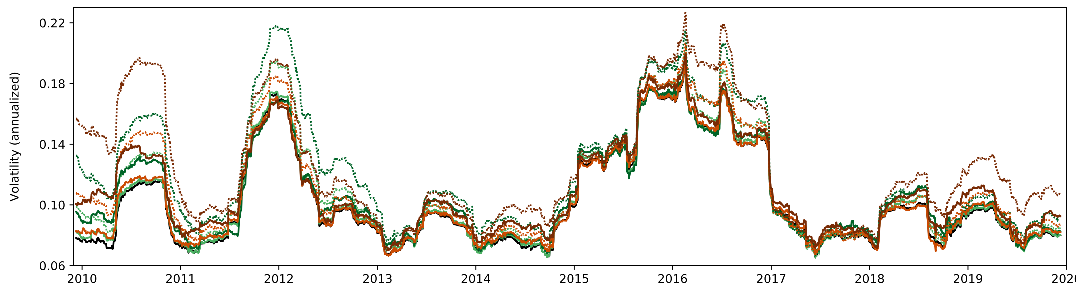
provides a risk-return ratio that only accounts for downside risk. Larger values of the Sortino ratio correspond to higher returns for a particular level of downside volatility. The best Sortino ratios are achieved by the two dark green strategies, followed by the green strategies and the minimum variance strategy. Brown and dark brown ESG constraints decrease the Sortino ratio. The same holds for the equally-weighted strategy, which has the lowest ratio of all strategies. Lastly, Table 4 gives the 95% and 99% daily value-at-risk (VaR) measures, which respectively represent the 5% and 1% worst daily returns. For both confidence levels, the highest similarity strategies with extreme ESG constraints (i.e. dark green and dark brown) have the lowest VaR.

In general, the results in Table 4 show that the green minimum variance strategy has the most similar risk and return behavior compared to the reference minimum variance strategy. The dark green, brown and dark brown minimum variance strategies yield higher returns at a cost of higher volatility and VaR levels. The same comparison holds for the highest similarity strategies, notwithstanding the fact that they bear generally more risk and yield lower returns than their minimum variance counterparts. However, note that the higher risks and lower returns of the highest similarity strategies follow from their construction as they do not minimize risk, but rather distance to the minimum variance portfolio.

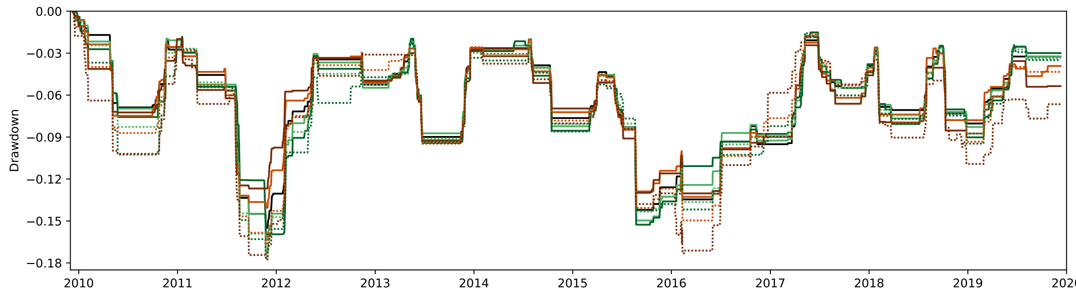
The aforementioned characteristics only assess the performance over the entire investment period. A deeper understanding of the behavior of the strategies is gained by evaluating time-dependent risk and performance measures throughout the lifetime of the strategies, as depicted in Figures 7 and 8. Figure 7a shows the evolution of the portfolio concentration by means of the ENC. First of all, we observe that there is not one strategy with an overall lower degree of concentration. That being said, it is clear



(a) Effective number of constituents.



(b) Six-months historical volatility.



(c) Six-months drawdown.

Figure 7: Evolution of risk measures for the different STOXX 600 strategies.

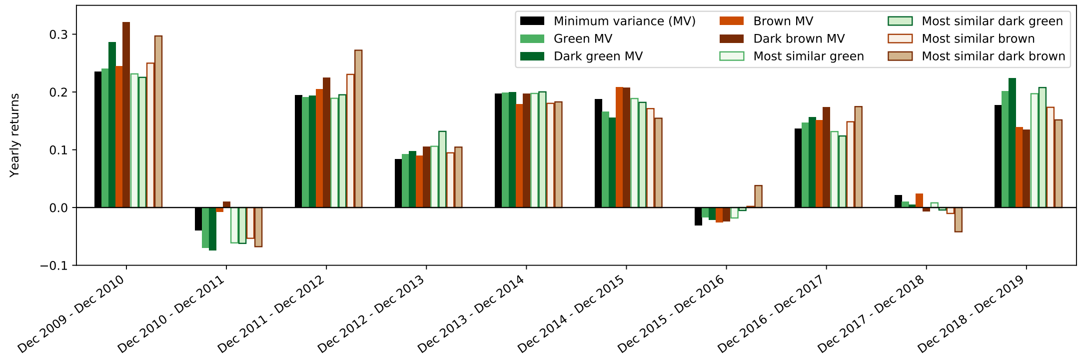
that the highest similarity strategies have a dominantly larger ENC value, meaning that they dictate to hold less concentrated portfolios. Figure 7b presents the annualized six-months realized volatility[3]. In times of high volatility, the highest volatilities are realized by the highest similarity strategies, and in particular by the dark green and dark brown version of it. When only considering the constrained minimum variance strategies, i.e. the solid lines, we find that their realized volatilities are fairly close to that of the reference minimum variance strategy. For instance, the six-months historical volatility of the green minimum variance strategy exceeds that of the minimum variance reference with at most 68 basis points throughout the entire investment period. Figure 7c shows the maximum drawdown in the preceding six months, which clearly agrees with the six-months historical volatility. Again, the most severe drawdowns are realized by the highest similarity strategies.

Figure 8a presents the total returns per investment year[4]. In the first three years, brown strategies clearly outperformed the others, while the green strategies had similar

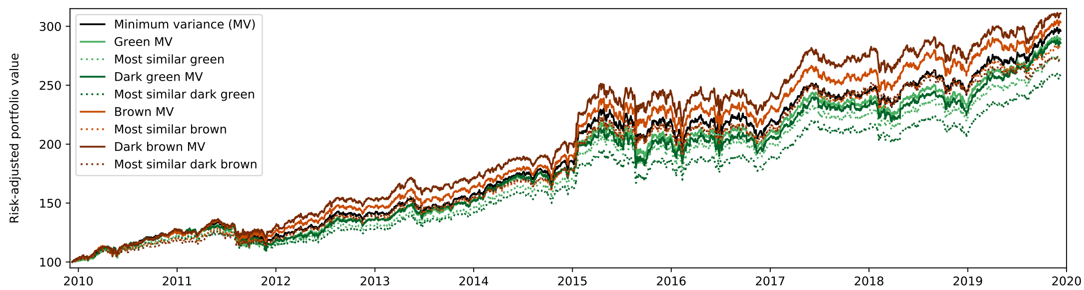
[3] Volatilities plotted for dates prior to June 2010 take into account the strategy's behavior before December 2009.

[4] The sole reason for plotting the returns along two columns is improved visibility.

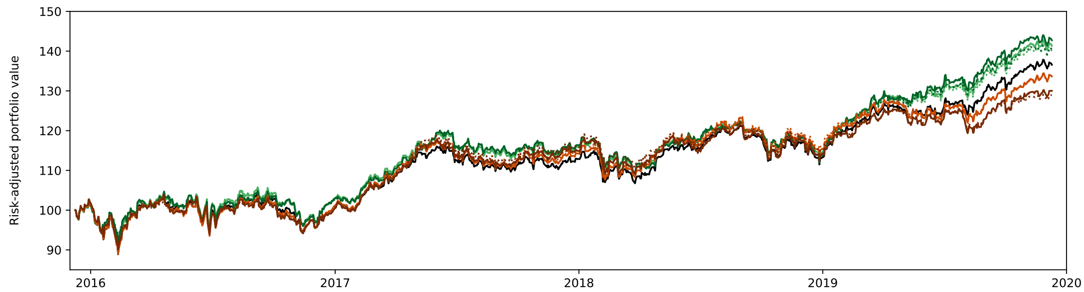
to worse returns compared to the reference minimum variance approach. This pattern based on ESG criteria seems to disappear in the following years, up to 2019. In this last year of the study, strategies with green ESG requirements generated higher returns than the minimum variance reference, while each of the brown strategies resulted in a lower return. However, one should keep in mind that these returns do not account for the risk being taken. Figure 8b presents the risk-adjusted cumulative returns with respect to the minimum variance strategy. Risk-adjusted daily net returns r_j^{RA} of strategy j are



(a) Total returns.



(b) Risk-adjusted cumulative returns.



(c) Risk-adjusted cumulative returns (base December 2015).

Figure 8: Evolution of performance measures for the different STOXX 600 strategies.

computed as

$$r_j^{RA} = r_j \cdot \frac{\sigma_{6M,MV}}{\sigma_{6M,j}} \tag{22}$$

where r_j denotes the daily net return of strategy j, $\sigma_{6M,MV}$ is the six-months historical volatility of the minimum variance strategy and $\sigma_{6M,j}$ is the six-months historical volatility of strategy j. Scaling by the volatility ratio hence lowers the returns of strategies that are more risky than the minimum variance strategy and vice versa. The risk-adjusted returns in Figure 8b seem to reveal a clear pattern: the darker green (brown) the ESG restrictions, the lower (higher) the risk-adjusted return. This observation must however be interpreted with care. Indeed, Figure 8a revealed that most brown returns were cashed in the early years. To clarify this point, let us assume we initiate the investment strategies in December 2015, i.e. right after the introduction of the United Nations Sustainable Development Goals [13] and the adoption of the Paris Agreement [14]. The cumulative risk-adjusted returns according to this starting point are depicted in Figure 8c. Between December 2015 and December 2018, risk-adjusted cumulative returns almost overlap for the nine different strategies. It seems that including ESG information in the allocation procedure does not provide added value when taking into account the risks that come with it. Starting from 2019, however, the risk-adjusted returns diverge in favor of the green strategies. The curves are moreover ordered from dark brown to dark green, where green strategies outperform both the minimum variance reference and their brown counterparts. This might be caused by the increased popularity of ESG investing.

3.2 The American market: Russell 1000

We repeat the analysis in the previous section for the American stock market, represented by the assets in the Russell 1000 index[5], and compare the results to those obtained for the European market.

3.2.1 The efficient frontier

We construct efficient frontiers on the same allocation date as in the European market study. Hence, expected returns and covariances are estimated on time series of historical daily returns[6], covering a two-year period prior to 10 September 2019. The investment universe is restricted to the 914 assets in the Russell 1000 index for which there is both historical return data and current ESG rating data at our disposal.

Figure 9 presents the positively restricted efficient frontiers, i.e. the solution of (5) with constraints

$$\mathbf{ESG}^t \boldsymbol{w} \geq \gamma_P \qquad \gamma_P = 5,\, 5.25,\, \ldots,\, 7.25, \tag{23}$$

where

$$\mathbf{ESG} = (\mathrm{ESG}_1, \ldots, \mathrm{ESG}_{914})^t \tag{24}$$

are the ESG scores of the assets in the universe, reported on 10 September 2019. Note that these ESG constraints are set lower than those in the European study in (10), since American companies generally have lower ESG scores than European companies. Indeed, the ESG scores reported on 10 September 2019 range from 1.80 to 7.50 for the American universe and from 2.40 to 8.10 for the European universe, with average scores of respectively 4.73 and 5.60. This is also reflected in the (unconstrained) minimum variance portfolio, which has in the American universe an ESG score of only 4.46. Figure 9 shows again that a modest rise in the portfolio ESG score does not shift the efficient frontier a lot, as long as the targeted expected return is not too high. Considering only the minimum variance portfolios represented by the bullets, we observe an increasing trend in the expected returns when green constraints become stronger.

[5]The investment universe includes the constituents of the Russell 1000 index as of March 2020. We do not see survivorship bias as a problem, as we only compare within the same data set.

[6]Returns are based on dividend-adjusted closing prices (in USD).

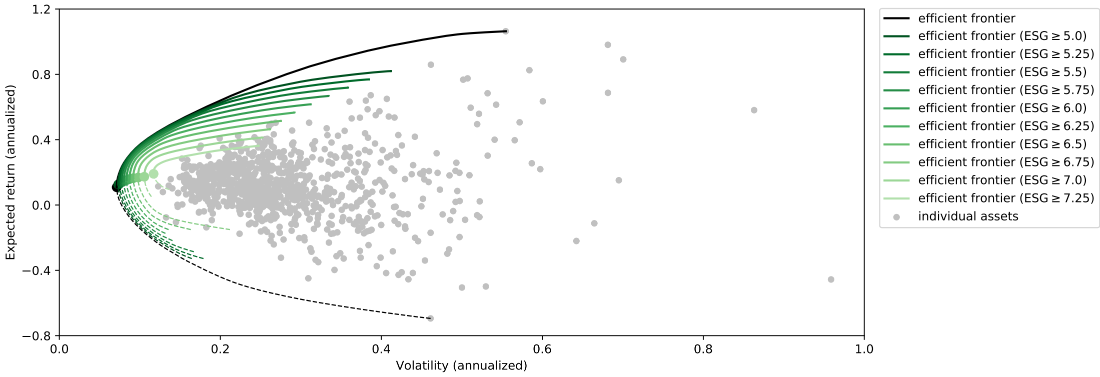


Figure 9: Mean-variance efficient Russell 1000 portfolios subject to positive ESG rating constraints.

Similarly, the efficient frontier is shifted towards a brown ESG score by setting the constraints as follows:

$$\mathbf{ESG}^t \boldsymbol{w} \leq \gamma_P \qquad\qquad \gamma_P = 2,\, 2.25,\, \ldots,\, 4. \tag{25}$$

Solving problem (5) accordingly results in the brown efficient frontiers in Figure 10. In this case, the distance between the shifted frontiers is larger, meaning that the constraints have a larger impact on the portfolio allocation. Ignoring the diversification effect, this could indicate that the 2-year historical performance of companies with lower ESG scores is worse in mean-variance sense compared to more sustainable companies in the universe. Furthermore, the expected return of the minimum variance portfolio drops when stronger brown constraints are enforced, while the opposite effect was observed for green ESG constraints in Figure 9.

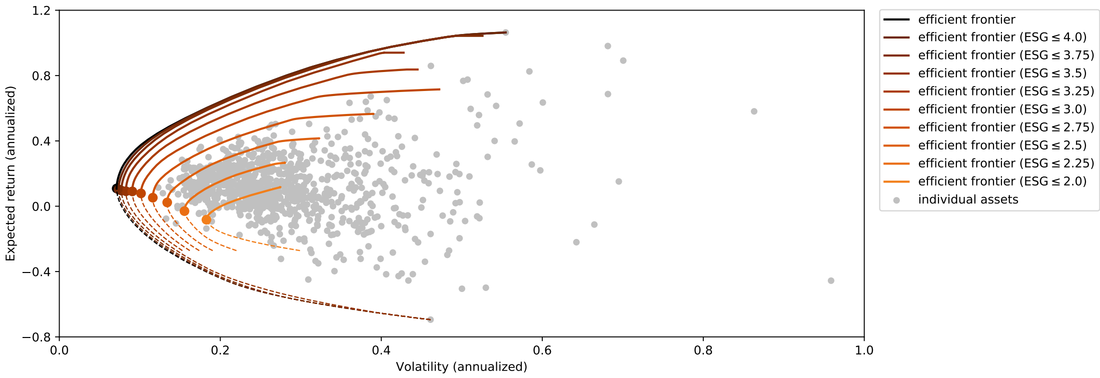


Figure 10: Mean-variance efficient Russell 1000 portfolios subject to negative ESG rating constraints.

Table 5 lists the expected returns, volatilities and ENC values for both green and brown constrained minimum variance portfolios. It turns out that green constrained portfolios are less concentrated when mild green ESG restrictions are imposed. In the STOXX 600 study in Table 1, this effect was only observed for mild brown restrictions. Although it might be just a coincidence, in both universes the concentration level is minimal when the target ESG score is approximately equal to 5. Regarding the expected returns, we observe that there is a monotonically increasing (decreasing) trend for green (brown) constraints. In other words, the greener the portfolio, the higher the

constraint	σ_{GMV}	μ_{GMV}	ENC	constraint	σ_{BMV}	μ_{BMV}	ENC
–	7.13%	10.88%	17.75	–	7.13%	10.88%	17.75
ESG $\geq$ 5	7.32%	12.57%	19.82	ESG $\leq$ 4	7.36%	10.27%	13.85
ESG $\geq$ 5.25	7.48%	13.21%	18.96	ESG $\leq$ 3.75	7.72%	9.59%	12.60
ESG $\geq$ 5.5	7.73%	13.92%	18.02	ESG $\leq$ 3.5	8.28%	9.18%	12.39
ESG $\geq$ 5.75	8.01%	14.59%	15.99	ESG $\leq$ 3.25	9.07%	9.09%	11.18
ESG $\geq$ 6	8.34%	15.22%	13.72	ESG $\leq$ 3	10.15%	7.86%	10.42
ESG $\geq$ 6.25	8.72%	15.91%	11.80	ESG $\leq$ 2.75	11.62%	5.24%	9.11
ESG $\geq$ 6.5	9.18%	16.43%	9.61	ESG $\leq$ 2.5	13.40%	2.31%	6.67
ESG $\geq$ 6.75	9.79%	16.83%	7.35	ESG $\leq$ 2.25	15.55%	-2.98%	4.66
ESG $\geq$ 7	10.56%	17.30%	5.47	ESG $\leq$ 2	18.28%	-8.25%	3.26
ESG $\geq$ 7.25	11.71%	19.08%	3.43				

Table 5: Properties of minimum variance Russell 1000 portfolios with various constraints on the ESG score.

expected return and vice versa. This was not found for the European universe in Table 1, where this pattern only holds for weak ESG constraints. Lastly, volatilities increase when restrictions become stronger, both for positive and negative constraints. However, volatilities rise sharper for brown constraints, which was also observed in Table 1.

Next, the green frontier of the Russell 1000 universe is computed by solving (6) with ESG targets

$$\mathbf{ESG}^t \boldsymbol{w} = \gamma_P \qquad\qquad \text{for } \gamma_P \in \big[\text{ESG}_{\text{MV}},\ \max\{\mathbf{ESG}\}\big], \tag{26}$$

where $\text{ESG}_{\text{MV}} = 4.46$ is the ESG score of the minimum variance portfolio. The green frontier in Figure 11 takes the same hook-shaped form as the green frontier of the STOXX 600 universe, meaning that lifting the portfolio ESG score does not necessarily require a lot of additional risk. To shift the ESG score from 4.46 to 5, for instance, one only needs 18 basis points of additional volatility.

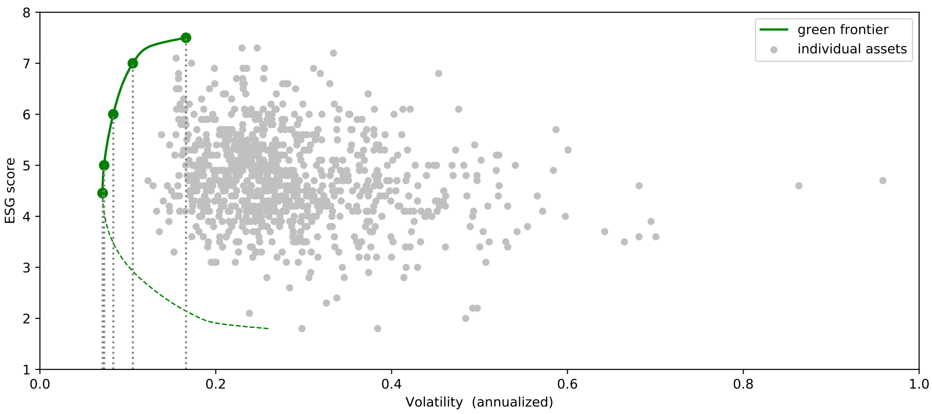


Figure 11: Green frontier of the Russell 1000 universe on 10 September 2019.

Table 6 lists the volatility, expected return and ENC for a selection of portfolios on the green frontier. We observe some differences with respect to the values in Table 2. Whereas the expected returns of portfolios on the European green frontier followed a hump-shaped curve, they increase in this case monotonically with the ESG rating. A similar, but reversed effect is observed for the ENC, which humps when the ESG rating

ESG	$\sigma_{\mathbf{GV}}$	$\mu_{\mathbf{GV}}$	ENC
4.46	7.13%	10.88%	17.75
5	7.31%	12.56%	19.71
5.5	7.72%	13.91%	17.91
6	8.35%	15.22%	13.76
6.5	9.18%	16.43%	9.61
7	10.57%	17.30%	5.46
7.5	16.62%	23.47%	1.00

Table 6: Properties of Russell 1000 portfolios on the green frontier.

increases, while being monotonically decreasing for the European universe. Both effects correspond with our findings in the left pane of Table 5.

Finally, Figure 12 presents the most similar efficient frontiers that satisfy the ESG requirements

$$\mathbf{ESG}^t \boldsymbol{w} \geq \gamma_P \qquad \gamma_P = 5,\, 5.5,\, \ldots,\, 7. \tag{27}$$

We observe that the portfolios that are most similar to the minimum variance portfolio, marked by the bullets, have expected returns that increase with the strength of the ESG constraints. The most similar frontiers are shifted further away from the minimum

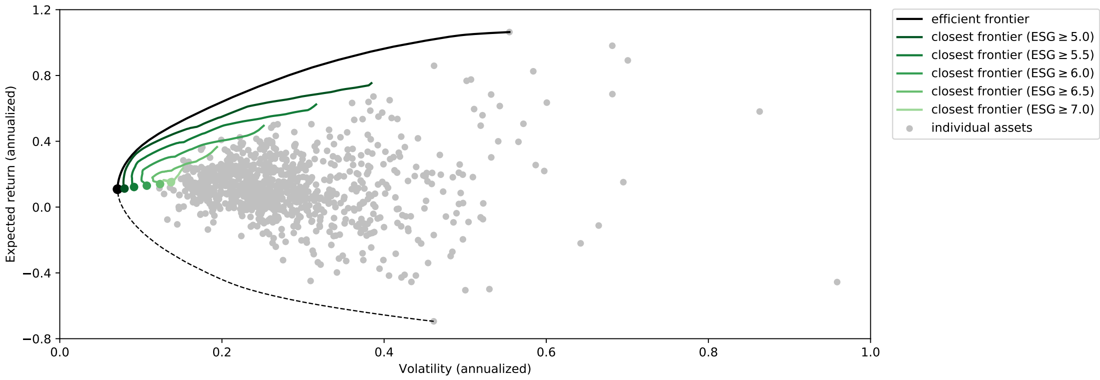


Figure 12: Green Russell 1000 portfolios that are most similar to those on the classical efficient frontier.

variance reference compared to the restricted frontiers in Figure 9. This is confirmed by the returns and volatilities reported in Table 7. Indeed, for the same constraints, we find both higher volatilities and lower returns than those in Table 5. On the other hand, the ENC values imply that the most similar portfolios are considerably less concentrated

constraint	$\sigma_{\textbf{ms-G}}$	$\mu_{\textbf{ms-G}}$	ENC
ESG ≥ 5	7.98%	11.26%	23.23
ESG ≥ 5.5	9.16%	12.20%	30.23
ESG ≥ 6	10.74%	13.02%	37.20
ESG ≥ 6.5	12.37%	14.01%	36.63
ESG ≥ 7	13.72%	15.13%	18.52

Table 7: Properties of the minimum variance Russell 1000 portfolios on the most similar green efficient frontier.

than both the constrained minimum variance portfolios in Table 5 and the portfolios on the green frontier in Table 6.

3.2.2 ESG investment strategies

We evaluate the ESG investment strategies defined in Section 3.1.2 for the American market universe based on the Russell 1000 index. The strategies are executed during the same period of approximately ten years with quarterly portfolio rebalancing. The investment universe consists of those assets in the Russell 1000 index as of March 2020, for which there is both return data and ESG information available on the rebalancing date. The number of assets in the investment universe evolves over time as depicted by the red line in Figure 13. Starting with only 406 assets, the universe steadily expands up to 914 assets in September 2019.

!

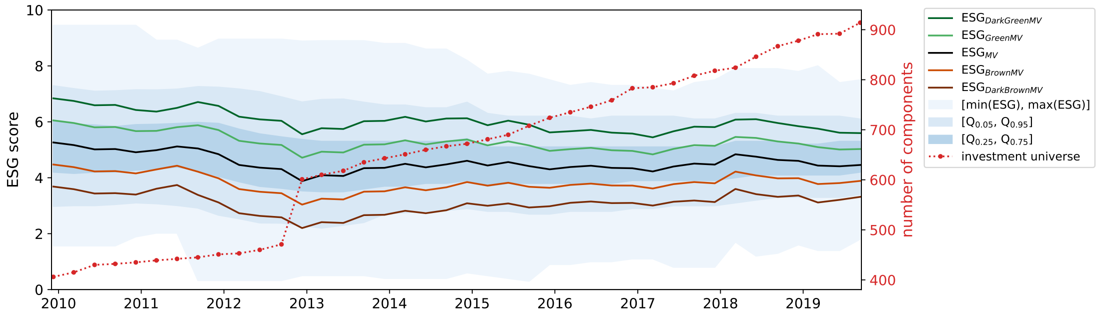


Figure 13: Left axis: portfolio ESG scores corresponding to the minimum variance Russell 1000 allocation strategies. Right axis: number of portfolio constituents.

The strategies are executed according to the sustainability requirements in Equation (16), i.e. based on the ESG score of the minimum variance portfolio and the range of ESG scores in the universe. The black line in Figure 13 depicts the ESG score of the minimum variance portfolio on each rebalancing day throughout the entire investment period, which fluctuates between 3.88 and 5.26. The blue areas sketch the distribution of ESG scores in the American investment universe. As in the European universe, the range of the scores reduces over time.

Figure 14 shows the out-of-sample performance of all strategies, as well as the performance of the equally-weighted strategy. The black line represents the reference minimum variance strategy, without incorporating ESG rating constraints. A couple of remarks can be made about these cumulative returns. First of all, the performance of the constrained minimum variance strategies can be ordered by color throughout the largest part of the ten-year period: the stronger the brown ESG rating constraints, the higher the returns; the stronger the green ESG rating constraints, the lower the returns. However, we observe that the dark green solid line is catching up with the green line in the last years of the investment period. Secondly, the returns of green minimum variance strategies do not coincide with the minimum variance reference - as opposed to the results in the European universe - but stay well below these reference returns. On the other hand, the most similar green and dark green strategies closely resemble the minimum variance reference. Lastly, we find that the most similar brown strategies yield lower returns compared to their constrained minimum variance counterparts. The same effect was observed for brown STOXX 600 strategies in Figure 6.

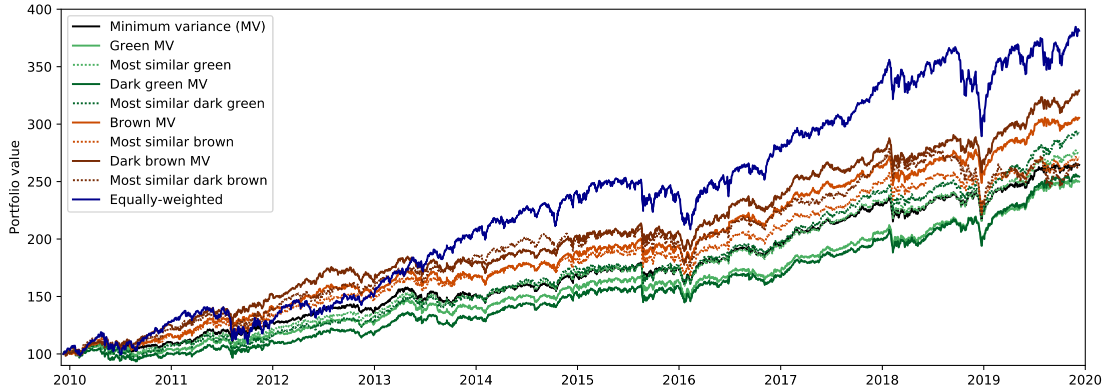


Figure 14: Historical performance of various Russell 1000 allocation strategies.

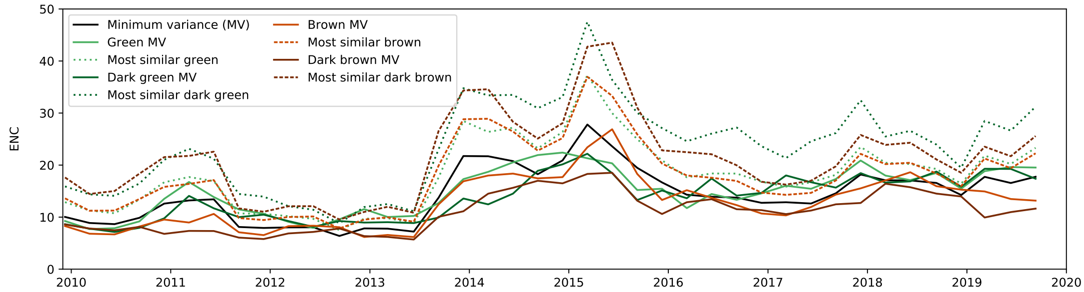
Table 8 evaluates performance and risk measures for the strategies. The overall (ten-year) MDD takes the lowest value for both the brown minimum variance strategy (BMV) and the reference minimum variance strategy (MV). The highest similarity strategies incur the largest drawdowns - only the equally-weighted strategy performs worse. This was also found for the European universe in Table 4. The annualized return takes

	MV	**GMV**	**ms-G**	**DGMV**	**ms-DG**	**BMV**	**ms-B**	**DBMV**	**ms-DB**	**EW**
MDD	-10.79%	-11.30%	-11.75%	-11.44%	-14.90%	-10.79%	-13.53%	-11.32%	-20.56%	-22.71%
Annualized return	10.22%	9.59%	10.68%	9.78%	11.35%	11.81%	10.49%	12.66%	10.30%	14.32%
Annualized volatility	9.77%	9.90%	10.56%	10.27%	11.79%	9.92%	10.94%	10.53%	12.92%	15.92%
Sortino ratio	1.49	1.38	1.36	1.68	1.71	1.44	1.37	1.37	1.16	1.30
1-day $\mathrm{VaR}_{0.95}$	-0.96%	-0.96%	-1.03%	-0.98%	-1.16%	-0.98%	-1.08%	-1.02%	-1.28%	-1.58%
1-day $\mathrm{VaR}_{0.99}$	-1.66%	-1.68%	-1.86%	-1.74%	-2.08%	-1.60%	-1.89%	-1.75%	-2.35%	-2.87%

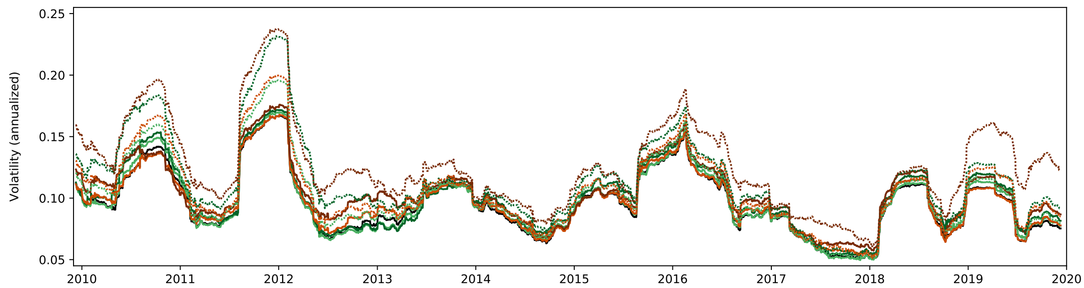
Table 8: Risk and performance statistics of all Russell 1000 strategies based on the entire investment period (December 2009 - December 2019).

the largest value for the brown minimum variance strategies (BMV and DBMV). On the other hand, green minimum variance strategies (GMV and DGMV) yield lower returns than those of the minimum variance reference. Highest similarity strategies have returns that outperform the minimum variance reference, but stay below those of the brown minimum variance strategies. The annualized ten-year realized volatility takes the lowest value of 9.77% for the unconstrained minimum variance strategy. It turns out that highest similarity strategies have higher volatilities than their minimum variance counterparts, which was also the case in the European study. More specifically, the green and brown constrained minimum variance strategies (GMV and BMV) have a volatility that exceeds the volatility of the minimum variance reference with at most 15 basis points, while stronger constraints lead to volatilities up to 76 basis points above the reference. The Sortino ratio reveals that the dark green strategies (DGMV an ms-DG) have again the highest returns for a given budget of downside risk. In fact, these two strategies are the only ones that outperform the minimum variance strategy in terms of Sortino ratio. Lastly, Table 8 states the 95% and 99% daily value-at-risk (VaR) measures, which confirm that the highest similarity strategies bear more risk than the constrained minimum variance strategies and show that green and brown minimum variance strategies have almost the same daily risk as the minimum variance strategy.

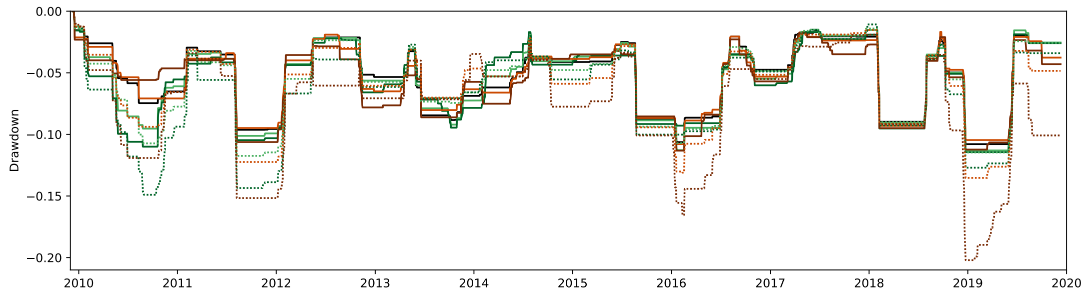
Figure 15 compares the risk and portfolio concentration characteristics of all strategies. In Figure 15a, which depicts the ENC of the portfolios, the same patterns can be observed as for the European universe. Indeed, the highest similarity strategies lead



(a) Effective number of constituents.



(b) Six-months historical volatility.

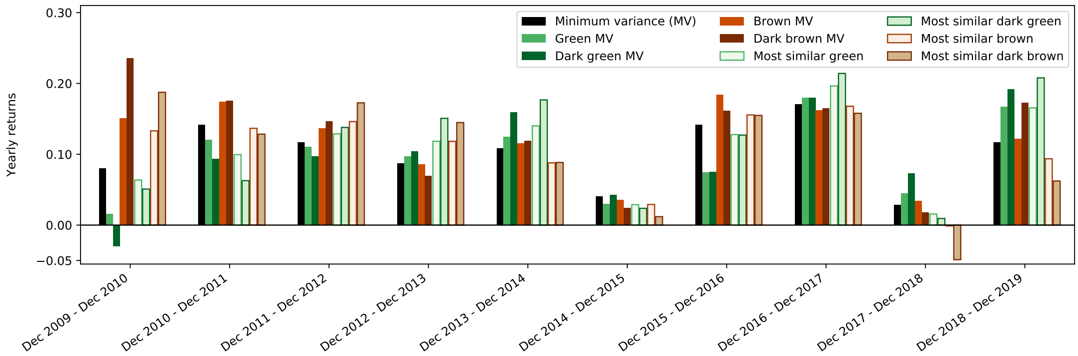


(c) Six-months drawdown.

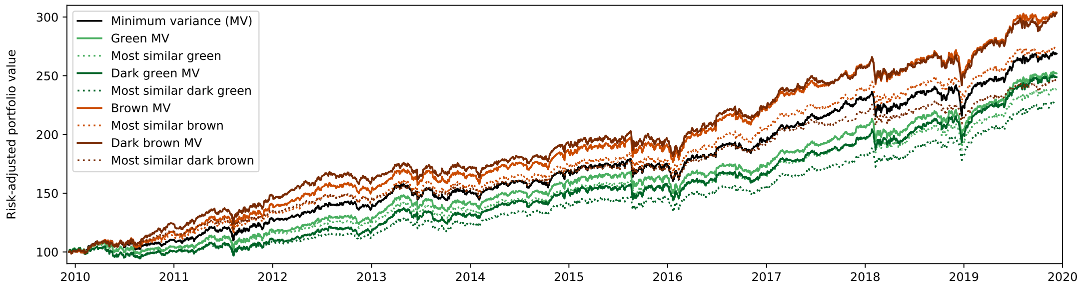
Figure 15: Evolution of risk measures for the different Russell 1000 strategies.

to the least concentrated portfolios throughout the largest part of the investment period. We moreover do not observe an overall difference in concentration level between green, brown or unconstrained portfolios. Figure 15b presents the six-months volatility realized by each of the strategies. The volatilities of the constrained minimum variance strategies are all fairly similar to the minimum variance reference, only the dark brown strategy has periods of significantly higher volatility. On the other hand, the six-months historical volatility of the green minimum variance strategy exceeds the the volatility of the minimum variance reference with at most 73 basis points throughout the entire investment period. Figure 15c presents the six-months drawdowns. Highest similarity strategies, and in particular the dark brown version, experience the most severe drawdowns. However, we again do not observe a clear order based on the type of ESG constraints.

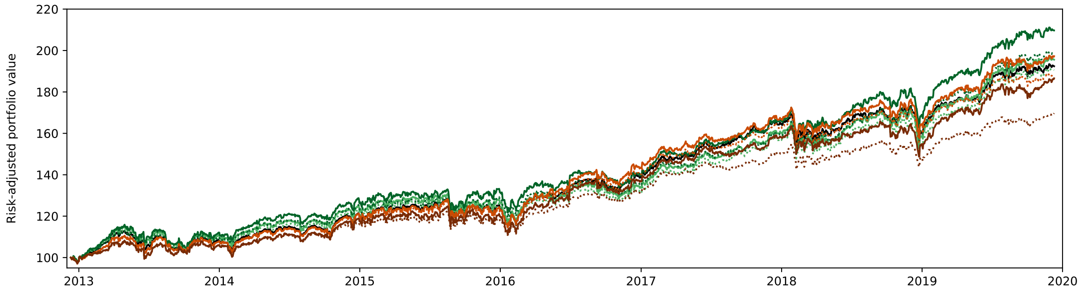
Figure 16 gives more insight in the returns generated by the strategies. Between December 2009 and December 2012, the yearly returns in Figure 16a are consistently ordered by greenness from dark green to dark brown, the latter generating the highest returns. The same order was found in Figure 8a for the European universe. In the following years, the order changes from year to year and we cannot draw a general



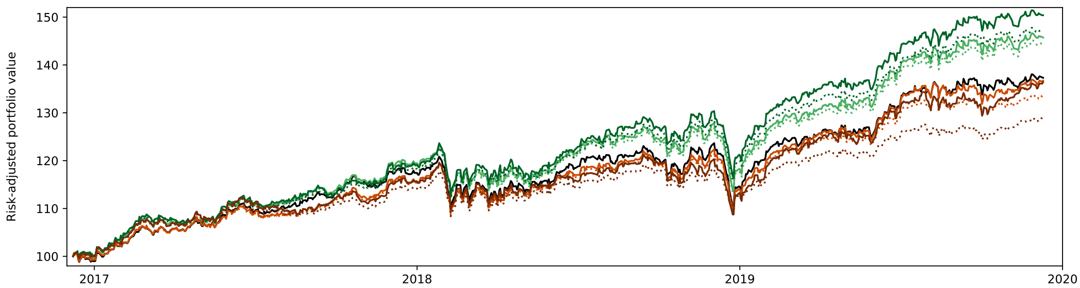
(a) Total returns.



(b) Risk-adjusted cumulative returns.



(c) Risk-adjusted cumulative returns (base December 2012).



(d) Risk-adjusted cumulative returns (base December 2016).

Figure 16: Evolution of performance measures for the different Russell 1000 strategies.

conclusion about the effect of green or brown constraints on the return of the strategy. In the last three years, however, green strategies outperformed the others and the returns can be ordered from dark brown to dark green, the latter corresponding to the highest returns. Throughout the entire investment period, risk-adjusted cumulative returns in Figure 16b are higher (lower) than those of the minimum variance reference when brown (green) ESG rating constraints are imposed. However, we observe that the gap between dark brown and brown strategies in Figure 14 has disappeared in Figure 16b due to the risk correction. As in the European universe, a large part of the brown returns has been generated in the first three years. Therefore, we examine in Figure 16c the cumulative risk-adjusted returns as of December 2012. This graph indeed shows that periods of green dominance are interchanged by periods in which brown strategies perform better. Since Figure 16a showed enhanced returns for the green strategies starting from 2017, we alternatively take December 2016 as starting point for the investments. In Figure 16d, the corresponding risk-adjusted returns show that even with risk-correction, strategies with green ESG constraints outperform both the minimum variance reference strategy and the brown alternatives starting from mid 2017. The European strategies revealed the same pattern towards green investing, but only as of 2019.

3.3 Divergence of ESG rating agencies

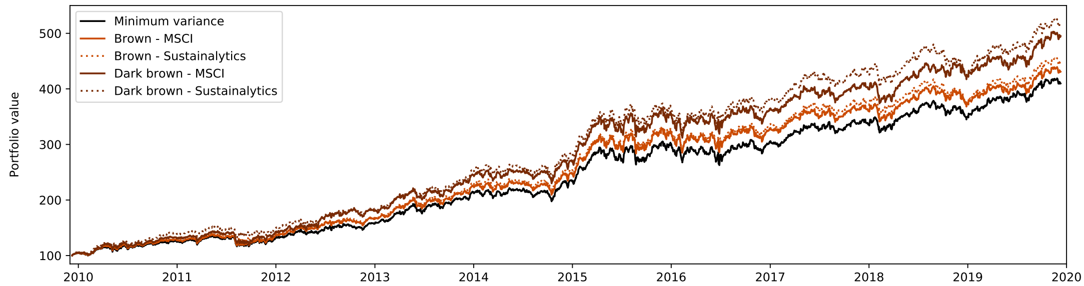
In the previous sections, we quantified ESG constraints by means of the weighted average key issue scores reported by MSCI. As criticized in the literature, however, ESG ratings from different rating agencies do not always agree. In this section, we therefore explore how much our findings change when ratings of another supplier are used. In particular, we rely on the ESG ratings published by Sustainalytics. Their scores are built in a similar fashion as the ones used in the MSCI study. More specifically, Sustainalytics measures the sustainability of a company based on 163 ESG-indicators across the three E, S and G pillars. A company-specific weight is assigned to each indicator in order to assess its importance for each company. We aggregate the raw scores and weights as follows,

$$\text{ESG score} = \sum_{i=1}^{163} \text{raw score}_i \cdot \text{weight}_i \tag{28}$$

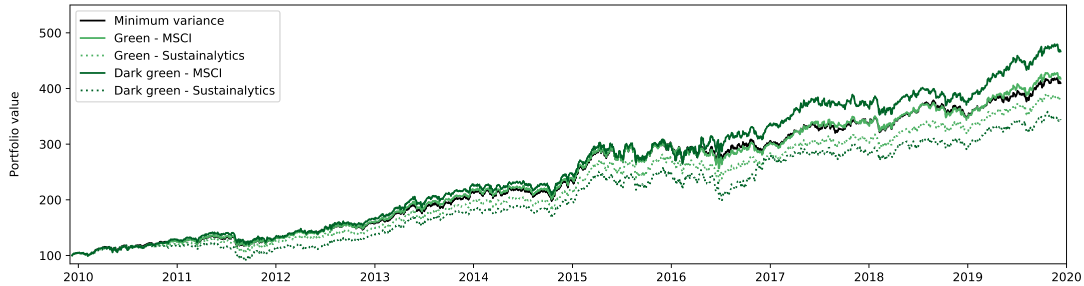
so that the ESG score is an overall company sustainability grade between 0 and 100. Companies with higher scores are assumed to have implemented better environmental, social and governance policies. Note that these scores reflect how well a company manages its ESG issues, not how much exposure it has to ESG-related risks. The data set used in this section consists of ESG scores reported on approximately the same dates as the ratings of MSCI. Hence, we again have quarterly ESG data ranging from December 2009 until December 2019.

We compare the ratings reported by Sustainalytics to those of MSCI, based on the performance of the ESG portfolio allocation strategies defined earlier. For this purpose, we consider the constrained minimum variance strategies, i.e. we solve (5) for the ESG rating constraints in Equation (16), where either the ratings of MSCI or Sustainalytics are used to characterize the greenness of an asset. Note that sustainability constraints were defined in a relative manner, such that the difference in scale between both ESG scores does not raise a problem. The analysis that follows is based on a limited market universe consisting of the EURO STOXX 50 constituents as of March 2020.

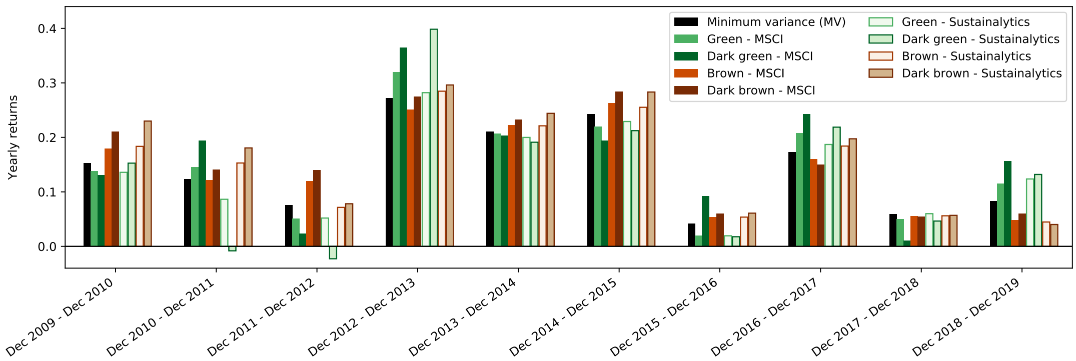
Figures 17a and 17b depict the cumulative returns of the brown and green constrained minimum variance strategies, respectively. We find that the impact of both green and brown constraints has been intensified by using ESG ratings provided by Sustainalytics instead of MSCI. Indeed, brown strategies - which all outperform the minimum variance reference - result in higher returns when ESG ratings of Sustainalytics have been used. On the other hand, we find that green strategies yield significantly lower returns when the greenness is defined by ESG scores of Sustainalytics, compared to MSCI. Moreover,



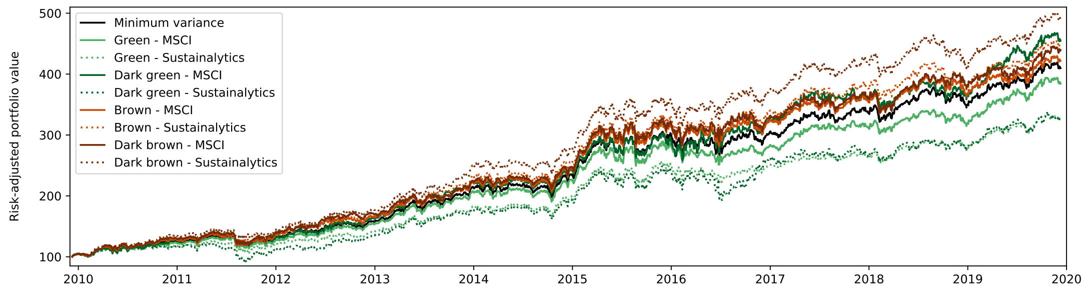
(a) Cumulative returns (brown constraints).



(b) Cumulative returns (green constraints).



(c) Total returns.



(d) Cumulative risk-adjusted returns.

Figure 17: Historical performance of minimum variance EURO STOXX 50 strategies with ESG rating constraints.

green strategies according to Sustainalytics are the only strategies that perform worse than the reference minimum variance strategy. In Figure 17c, we plot the total returns of the strategies in each investment year. The degree of correspondence between both rating agencies varies from year to year. It should be noted that, according to this graph, the returns generated by the strategies relying on Sustainalytics are not always more extreme than their MSCI counterparts. To take into account a notion of risk, we finally consider the risk-adjusted performance in Figure 17d. Even with risk-correction, we find considerable differences in the performance of ESG strategies defined by Sustainalytics versus MSCI.

4 GHG intensity as sustainability indicator

In this section, we quantify the environmental sustainability of a company by means of its greenhouse gas (GHG) emission intensity. The reason for this choice is twofold. First, when sustainability was measured by the ESG score of the portfolio, we did not find clear-cut evidence for enhanced performance of sustainable portfolios. While ESG scores reflect the opinion of a rating agency, GHG emissions are measurable - albeit a complicated task. Secondly, and more importantly, the choice for GHG emissions is grounded by the ambitions of the United Nations and the European Union to mitigate climate change. One of the initiatives to encourage companies to reduce their emissions is the introduction of climate benchmarks, proposed in the TEG final report on EU climate benchmarks and benchmarks' ESG disclosures ([7]).

We investigate the performance of portfolios that satisfy the main GHG emission reduction targets as required by the EU climate benchmarks. For this purpose, we express the quantity of GHG emissions in terms of CO_2-equivalent (CO_2e) emissions of all six greenhouse gases that are listed in the Kyoto protocol[7]. To account for the greenhouse effect of these gases, the volume of each gas is mapped to the volume of CO_2 that has an equivalent greenhouse effect. In the portfolio analysis that follows, we quantify the sustainability of a company by its GHG emission intensity, defined as

$$\text{GHG intensity} = \frac{\text{tCO}_2\text{e}}{\text{MCap}} \tag{29}$$

where tCO_2e stands for the scope 1 and scope 2 CO_2e emissions of the company (in tonnes per year) and MCap for its market capitalization (in million EUR). Note that the TEG report recommends to use enterprise value in the denominator of GHG intensity, as this "allows for the applicability of the methodology to both equity and/or fixed income investments and does not bias for or against any particular sector" ([7]). Since we purely focus on (the comparison of) equity portfolios, we can use market capitalization instead. In that case, the GHG intensity can be interpreted as the total scope 1 and 2 GHG emissions per million EUR invested in the company. Similarly, the GHG intensity of a portfolio is computed as the weighted average of the GHG intensities of its constituents and corresponds to the total GHG emission per million EUR invested in the portfolio.

For the empirical analysis, we follow the same approach as in Section 3. We start by constructing an unconstrained reference portfolio that does not take into account GHG emission data. Two different reference portfolios are considered; the minimum variance portfolio and the equally-weighted portfolio. Next, we construct portfolios with constraints on their GHG intensities, relative to the GHG intensity of the reference portfolio. Two of these constrained portfolios are based on the characteristics of the Climate Transition Benchmark (CTB) and the Paris-aligned Benchmark (PAB) proposed in the TEG report. To examine the impact of a negative GHG transition as well, we define a brown strategy that requires an emission increase. Hence, we consider for each

[7]Carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs) and sulphur hexafluoride (SF_6).

reference strategy three related GHG strategies that satisfy the conditions listed in Table 9. One can think of these three categories as different degrees of greenness, with the CTB-inspired portfolio considered green and the PAB-portfolio considered dark green.

	CTB	**PAB**	**Brown**
Scope 1 and 2 GHG intensity compared to reference portfolio	maximum 70%	maximum 50%	minimum 150%
Exposure constraints compared to reference portfolio	equal GICS sector exposure		equal GICS sector exposure
	equal or higher exposure to high climate impact sectors		equal or lower exposure to high climate impact sectors

Table 9: Summary of portfolio requirements for the different GHG strategies.

The first and most important condition aims for a reduction in GHG intensity for the CTB and PAB portfolio, while it increases the GHG intensity of the brown portfolio. These emission reductions/increases should be interpreted with respect to the reference portfolio, i.e. the minimum variance portfolio or the equally-weighted portfolio. Note that we only impose emission constraints on the portfolio as a whole and do not exclude particular assets. The second condition enforces two sector exposure constraints with as objective to ensure that high climate impact sectors are still part of the constrained portfolio and are hence affected by the GHG emission reduction target. According to the TEG report, a EU climate benchmark's exposure to high climate impact sectors (according to the NACE classification) cannot be less than the exposure of the reference universe to these sectors. Hence, we require the total weight of companies with NACE section code A, B, C, D, E, F, G, H or L (i.e. high climate impact companies) to be higher than or equal to the corresponding total weight in the reference portfolio[8]. Since the brown strategy aims for an emission increase, we enforce high-climate impact sectors to have a lower exposure in brown portfolios. We additionally require individual sector weights of the eleven sectors in the Global Industry Classification Standard (GICS) to be the same as those of the reference portfolio.

Since our portfolio analysis is performed on historical data, we do not incorporate the year-on-year self-decarbonization rate of 7% per annum. The objective of this analysis is rather to assign the initial impact of GHG emission constraints on the performance and risk behavior of a portfolio.

4.1 The European market: STOXX 600

In this section, we empirically analyze the impact of GHG emission intensity constraints on portfolios consisting of the assets in the STOXX Europe 600 index. The analysis is based on scope 1 and scope 2 GHG intensity data reported by MSCI ESG Research. Since emission data is updated once per year, usually in June[9], we only rebalance the portfolios yearly as of June 2009.

The red line in Figure 18 shows the number of companies in the universe for which there is both return data and emission data available on the rebalancing date. The blue

[8] The assignment of NACE section codes is performed with the NACE to GICS mapping provided in the Handbook on Climate Benchmarks and benchmark's ESG disclosures [8].

[9] GHG data published in June corresponds to the emissions of the previous calendar year.

areas represent the distribution of the GHG intensity for companies in the STOXX 600 universe. Note that the left y-axis has a logarithmic scale because the GHG intensity distribution is heavily right-skewed. For instance, GHG intensities reported in June 2019 range from 0.0020 to 9184.64 tCO_2e/MCap. This emphasizes the importance of including sector exposure constraints in the portfolio optimization. Indeed, a climate benchmark could easily be greenwashed by shifting the portfolio towards sectors with low GHG intensities, which discourages carbon intensive sectors to reduce their emissions.

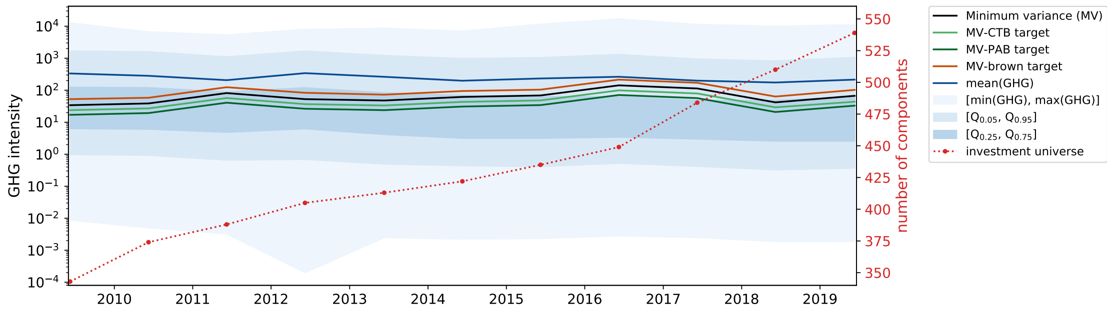


Figure 18: Left axis: GHG intensity of the companies in the STOXX 600 universe and their portfolios. Right axis: number of portfolio constituents.

The black line in Figure 18 presents the GHG intensity of the minimum variance portfolio $\boldsymbol{w}_{\mathrm{MV}}$, i.e.

$$\mathrm{GHG}_{\mathrm{MV}} = \mathbf{GHG}^t \boldsymbol{w}_{\mathrm{MV}} \tag{30}$$

where

$$\mathbf{GHG} = (\mathrm{GHG}_1, \ldots, \mathrm{GHG}_N)^t \tag{31}$$

are the GHG intensities of the companies in the investment universe. The GHG intensity of this reference portfolio fluctuates between 34 and 143 tCO_2e/MCap. In blue, we plotted the average GHG intensity, i.e. the GHG intensity of the equally-weighted portfolio. The other three lines depict the GHG intensity target for the CTB (green), PAB (dark green) and brown portfolio with respect to the minimum variance reference portfolio as required by the conditions in Table 9.

To allocate portfolios that meet the GHG requirements, we again rely on the constrained minimum variance strategy and the highest similarity strategy that were introduced in Section 3.1.2. Since we additionally consider the equally-weighted strategy as reference portfolio, we can distinguish three approaches:

1. **Minimum variance strategy (MV)**: invest in the minimum variance portfolio satisfying particular GHG intensity requirements, i.e. solve (5) with sustainability constraint

$$\mathbf{GHG}^t \boldsymbol{w} \ \leq \ c \cdot \mathrm{GHG}_{\mathrm{MV}}, \tag{32}$$

where c quantifies the required level of GHG reduction/increase. For the brown strategy, the inequality is reversed.

2. **Most similar to minimum variance strategy (MSMV)**: invest in the portfolio satisfying GHG intensity requirements with allocation (i.e weight distribution) that is most similar to the allocation of the unconstrained minimum variance portfolio, i.e. solve (8) subject to (32).

3. **Most similar to equally-weighted strategy (MSEW)**: invest in the portfolio satisfying GHG intensity requirements with allocation (i.e weight distribution) that is most similar to the allocation of the equally-weighted portfolio, i.e. solve (8) where $\boldsymbol{w}_{\mathrm{MV}}$ is replaced by $1/N$, subject to the sustainability constraint

$$\mathbf{GHG}^t \boldsymbol{w} \;\leq\; c \cdot \mathrm{GHG}_{\mathrm{EW}}, \tag{33}$$

with $\mathrm{GHG}_{\mathrm{EW}}$ the average GHG intensity of the companies in the universe. The inequality is again reversed for brown strategies.

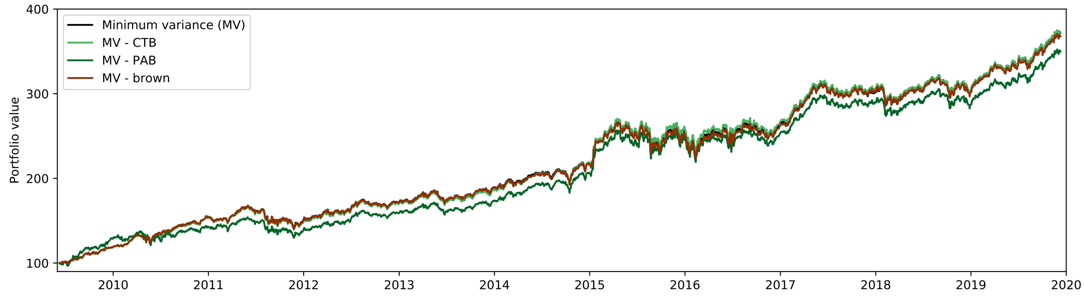
In each optimization procedure described above, we include the sector allocation constraints

$$\mathbf{1}_S^t \boldsymbol{w} \;=\; \mathbf{1}_S^t \boldsymbol{w}_{\mathrm{ref}} \qquad \text{for each GICS sector } S \tag{34}$$

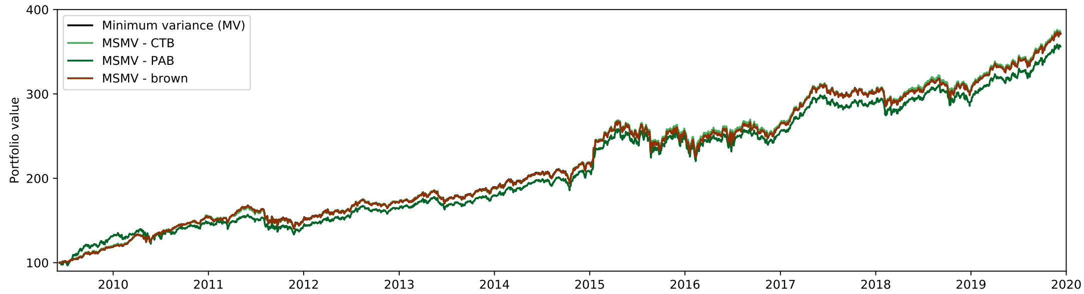
$$\mathbf{1}_{HC}^t \boldsymbol{w} \;\geq\; \mathbf{1}_{HC}^t \boldsymbol{w}_{\mathrm{ref}}, \tag{35}$$

where $\mathbf{1}_S$ is the indicator vector that takes value 1 on position i if company i belongs to GICS sector S and 0 otherwise, $\mathbf{1}_{HC}$ the indicator vector for companies belonging to a high-climate impact sector, and $\boldsymbol{w}_{\mathrm{ref}}$ is the allocation of the reference portfolio.

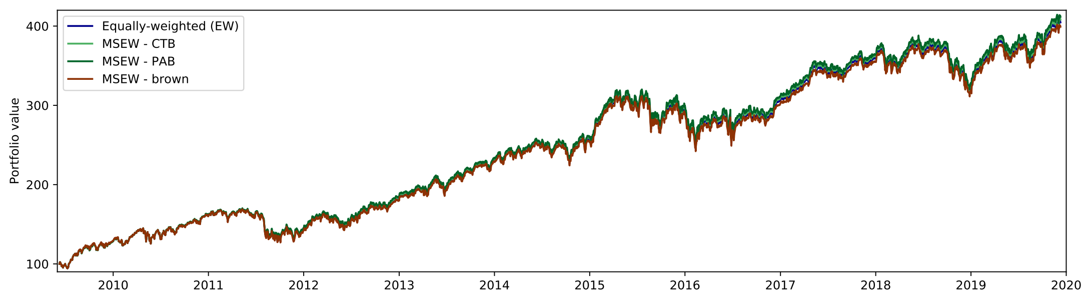
We evaluate the three strategies outlined above between June 2009 and December 2019, each according to the three levels of greenness, i.e. CTB (green), PAB (dark green) and brown. This results in the cumulative returns depicted in Figure 19.



(a) Constrained minimum variance strategies.



(b) Highest similarity strategies w.r.t. the minimum variance reference strategy.



(c) Highest similarity strategies w.r.t. the equally-weighted reference strategy.

Figure 19: Cumulative returns of STOXX 600 strategies with GHG intensity requirements.

Figure 19a and 19b both take the minimum variance strategy as reference. For these two graphs, we observe that the dark green PAB strategies yield lower returns compared to the green and brown strategies. Figure 19c presents the performance of the (most similar to) equally-weighted strategies. In this case, the cumulative returns are closer to each other compared to those in Figure 19a and 19b, and the PAB strategy yields slightly higher returns. The same conclusions can be made when looking at the returns generated in each year as depicted in Figure 20. It turns out that the dark green minimum variance based strategies lost most of their potential returns in the first two years, i.e. between June 2009 and June 2011. When focusing on the returns of the equally-weighted strategies indicated by the hatched bars, we find in 6 out of the 10 years that the brown strategy performs worse than the green and dark green strategy.

Table 10 gives more details about the overall riskiness and performance of the strategies. Besides the measures discussed in Tables 4 and 8, we also report the average portfolio ENC corresponding to the 11 rebalancing dates. From the minimum variance based strategies, only the dark green MV-PAB strategy invests on average in more concentrated portfolios than the minimum variance strategy itself. The portfolios of GHG constrained equally-weighted strategies are by construction more concentrated than the

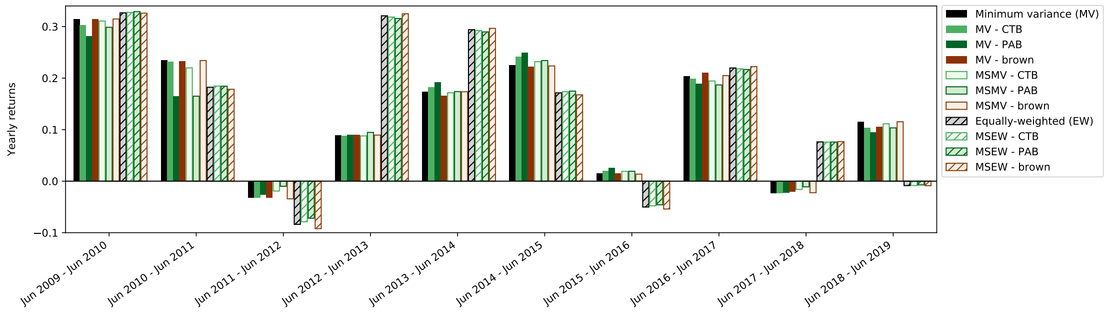


Figure 20: Yearly returns.

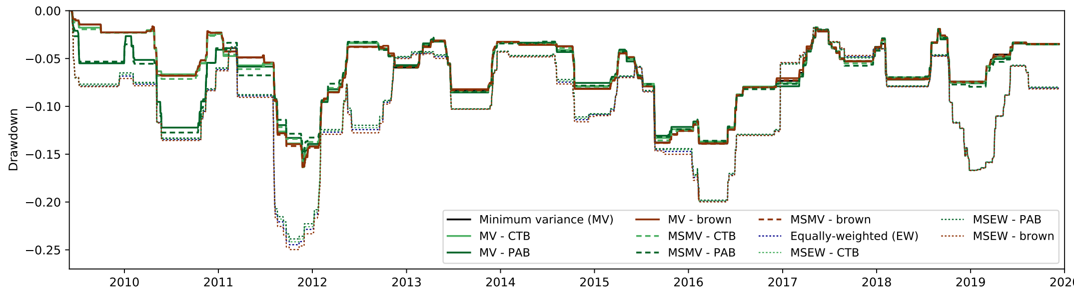
equally-weighted strategy itself; we find an average drop in ENC of maximum 3.27% and this for the MSEW-PAB strategy. A couple of further remarks can be made. First of all, we find that the maximum drawdown (MDD) is in most cases smaller when green constraints (CTB or PAB) are included, while brown constraints lead to more severe drawdowns. The annualized return of CTB portfolios is for each of the three strategies higher than the return of the reference, being either the minimum variance (MV) or the equally-weighted (EW) strategy. Further, all strategies based on the minimum variance portfolio have a realized volatility that is higher than the volatility of the minimum variance strategy itself. One can notice that the minimum variance based strategies with PAB characteristics (i.e. MV-PAB and MSMV-PAB) have a significantly larger volatility compared to the other strategies with minimum variance reference. This does not hold for the equally-weighted based portfolios, where both green and dark green GHG constraints reduce the volatility while the brown constraint increases it. Considering the Sortino ratio, we find that GHG strategies with respect to the minimum variance reference cannot outperform the reference. Both CTB strategies manage to attain the same risk-return ratio, while an emission reduction of 50% as required by the PAB strategies leads to a drop of 0.17 in the Sortino ratio. This does not hold for the equally-weighted strategies, where both emission reduction targets result in a higher Sortino ratio. Lastly, GHG constraints do not seem to have a significant impact on the value-at-risk (VaR), except when PAB constraints are imposed on minimum variance based strategies. In the latter case, the 95% VaR increases up to 10 basis points above the reference. It is finally worth mentioning that the highest similarity strategies with GHG constraints do

	MV	**MV-CTB**	**MV-PAB**	**MV-B**	**MSMV-CTB**	**MSMV-PAB**	**MSMV-B**
Average ENC	15.34	15.45	15.13	15.50	16.15	16.27	15.37
MDD	-16.28%	-16.35%	-15.78%	-16.30%	-15.72%	-14.99%	-16.49%
Annualized return	13.32%	13.33%	12.66%	13.21%	13.36%	13.86%	13.30%
Annualized volatility	10.77%	10.79%	11.49%	10.78%	10.81%	11.65%	10.79%
Sortino ratio	1.77	1.77	1.60	1.75	1.77	1.60	1.76
1-day $\text{VaR}_{0.95}$	-0.99%	-1.02%	-1.08%	-1.00%	-1.02%	-1.09%	-1.01%
1-day $\text{VaR}_{0.99}$	-1.82%	-1.81%	-1.89%	-1.83%	-1.83%	-1.90%	-1.82%
	EW	**MSEW-CTB**	**MSEW-PAB**	**MSEW-B**			
Average ENC	432.91	428.71	418.77	421.57			
MDD	-24.46%	-24.16%	-23.86%	-24.97%			
Annualized return	14.24%	14.33%	14.43%	14.09%			
Annualized volatility	16.54%	16.48%	16.41%	16.65%			
Sortino ratio	1.27	1.28	1.29	1.25			
1-day $\text{VaR}_{0.95}$	-1.60%	-1.61%	-1.60%	-1.64%			
1-day $\text{VaR}_{0.99}$	-2.83%	-2.84%	-2.83%	-2.89%			

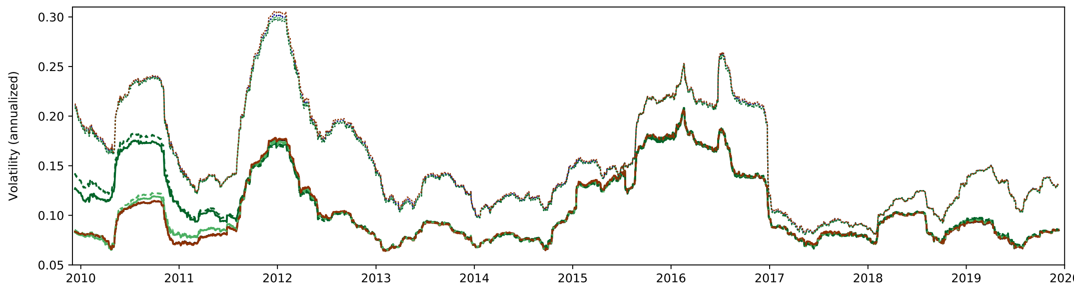
Table 10: Risk and performance statistics of the STOXX 600 strategies with GHG intensity constraints (June 2009 - December 2019).

not necessarily bear a higher risk than the constrained minimum variance strategies, as opposed to the strategies with ESG rating constraints in Section 3.

Figure 21 gives more insight in the evolution of the riskiness of each strategy, with the six-months drawdowns depicted in Figure 21a and the six-months realized volatilities in Figure 21b. Besides the fact that equally-weighted strategies incur larger drawdowns



(a) Six-months drawdown.



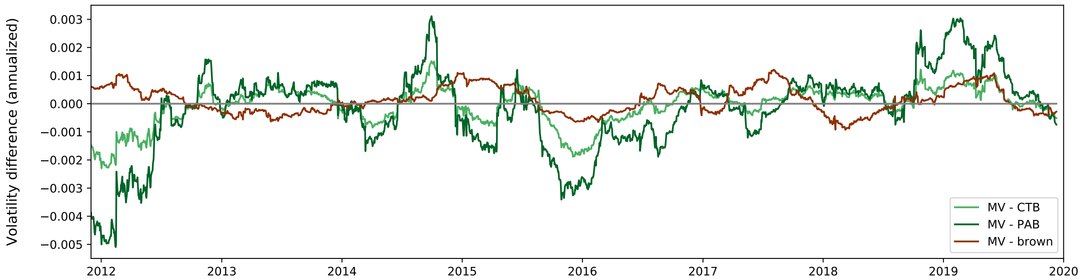
(b) Six-months realized volatility.

Figure 21: Risk characteristics of STOXX 600 strategies with GHG intensity requirements.

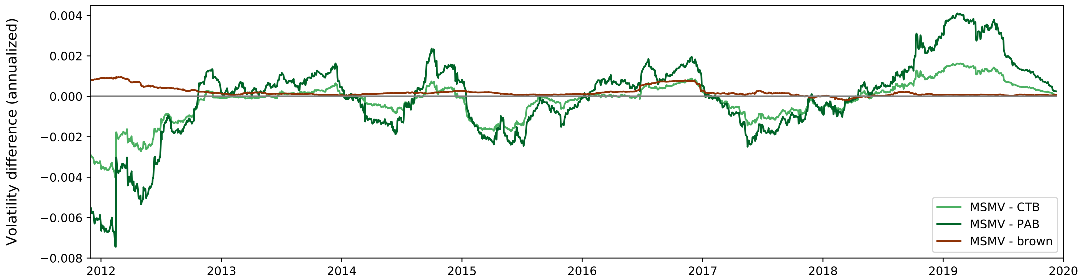
and have higher volatilities than minimum variance based strategies, we do not observe a lot of dissimilarities among the strategies. Both risk measures show that - starting from 2012 - the risks of including GHG intensity constraints on either the minimum variance or the equally-weighted strategy is rather limited. To quantify the amount of additional risk coming from the GHG constraints more carefully, we plot in Figure 22 the volatility difference with respect to the reference, i.e.

$$\sigma_{6M,j} - \sigma_{6M,ref}, \tag{36}$$

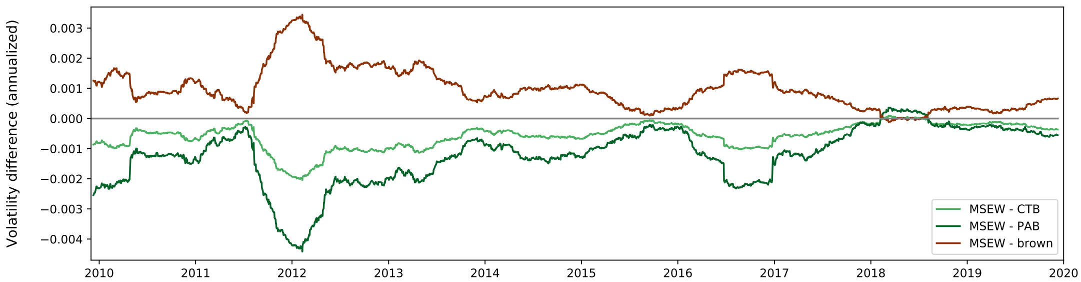
where j refers to the GHG constrained strategy of interest and ref to either the minimum variance or the equally-weighted reference strategy. Positive curves hence correspond to volatilities exceeding the volatility of the unconstrained reference strategy. Since Figure 21b showed that minimum variance strategies with PAB constraints had in the first two years a significantly higher volatility than the reference, we focus in Figures 22a and 22b on the volatilities as of January 2012. These two graphs show that the volatilities fluctuate around the reference volatility. Starting from 2012, the volatility of the MV-CTB portfolio exceeds the reference volatility with at most 15 basis points. Similarly, for PAB constrained strategies the difference in volatility equals at most 31 basis points. When considering the most similar minimum variance strategies, these numbers slightly increase towards respectively 16 and 41 basis points. On the other hand, it should be noted that the volatilities of the brown strategies, which require an increase in GHG intensity, exceed the minimum variance reference even less.



(a) Constrained minimum variance strategies.



(b) Highest similarity strategies w.r.t. the minimum variance reference strategy.



(c) Highest similarity strategies w.r.t. the equally-weighted reference strategy.

Figure 22: Additional realized volatility of STOXX 600 strategies due to the inclusion of GHG intensity constraints.

Figure 22c shows a completely different pattern for the equally-weighted strategies. Again, volatilities do not deviate more than 44 basis points from the reference, but in this case green and dark green GHG constraints lead to an overall reduced volatility - albeit a reduction of only a couple of basis points. Similarly, an increase in GHG intensity results in a higher realized volatility. One reason for this pattern could be the higher GHG intensity of the equally-weighted reference, which makes it easier to reduce emissions with respect to this reference compared to the minimum variance reference.

4.2 The American market: Russell 1000

The same analysis is carried out for a stock universe in the American market, consisting of the assets in the Russell 1000 index. Figure 23 presents the GHG intensities of the companies in this universe, as well as the GHG targets of the strategies that take the minimum variance portfolio as reference. The GHG intensity ranges from $1.20 \cdot 10^{-2}$ to $1.93 \cdot 10^{4}$, which is both narrower and higher compared to the range of GHG intensities in the European universe. Further, note that the target GHG intensities of the minimum variance based strategies are all between the 75% and 95% quantile of GHG intensities in the universe. In the European setting, these targets were lower with respect to the GHG range, with values between the 40% and 85% quantile. Recall that this shift is purely caused by the GHG intensity of the minimum variance portfolio, which turns out to be higher for the American market. One could interpret this as follows. A portfolio aiming for minimum risk (measured by volatility) requires relatively higher GHG intensities when it consists of American stocks instead of European stocks. In the American universe, the GHG intensity is on most rebalancing dates even higher than the average GHG intensity corresponding to the equally-weighted portfolio.

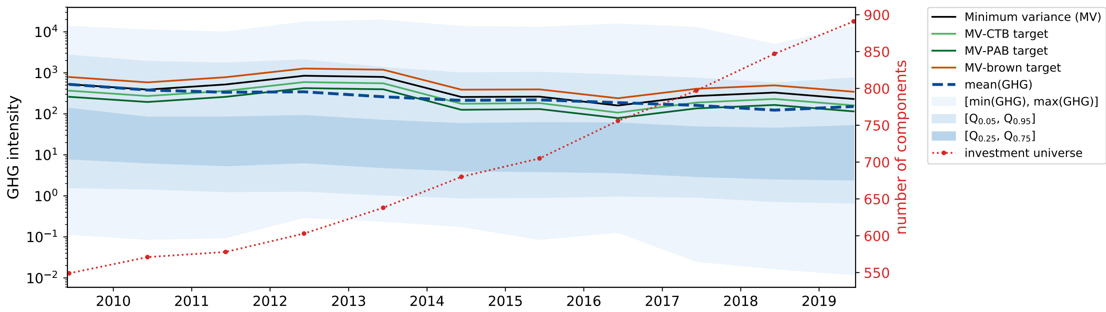
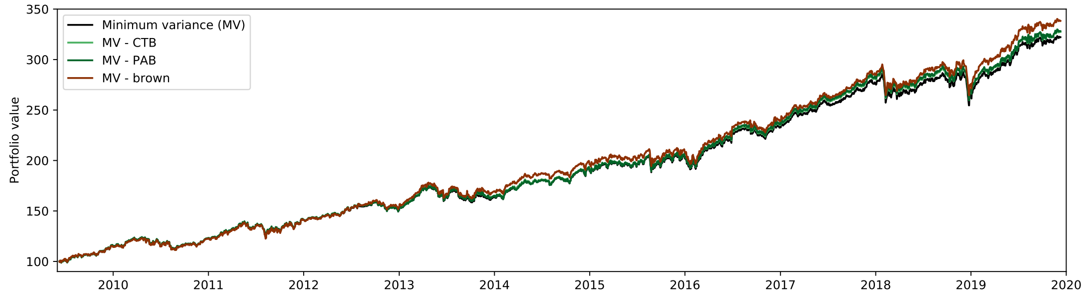


Figure 23: Left axis: GHG intensity of the companies in the Russell 1000 universe and their portfolios. Right axis: number of portfolio constituents.

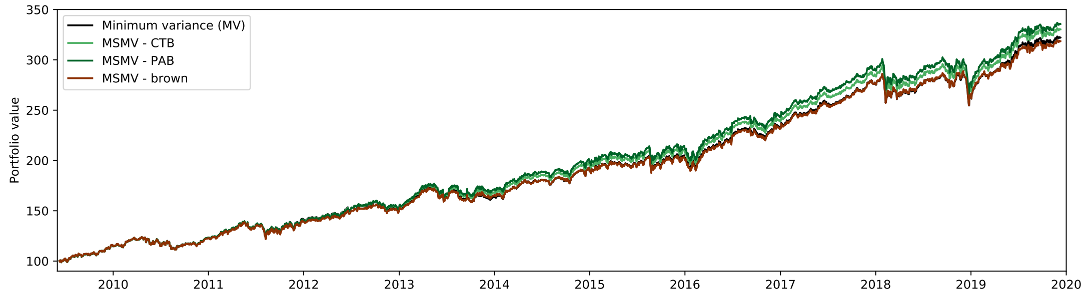
Figure 24 presents the cumulative returns for each of the three strategies (MV, MSMV, MSEW) according to the three levels of greenness (CTB, PAB, brown). GHG intensity constraints seem to have a different effect on the two minimum variance based strategies in Figures 24a and 24b. The brown constrained minimum variance strategy yields higher returns than the two green constrained strategies, but all GHG restrictions lead in the end to a higher cumulative return than the minimum variance strategy. Highest similarity strategies in 24b only generate higher returns when the GHG intensity is reduced with respect to the minimum variance reference, and the cumulative return of the brown MSMV strategy ends up below the reference. Equally-weighted strategies are relatively less affected by GHG constraints, which was also observed in the European study.

Figure 25 presents the returns generated per year up to June 2019. Compared to the returns of the STOXX 600 strategies in Figure 20, the green and dark green minimum variance based strategies do not yield lower returns in the first two years. The contribution of green and brown constraints varies for all strategies from year to year; in some years GHG reductions enhance performance, while in other years they yield lower returns.

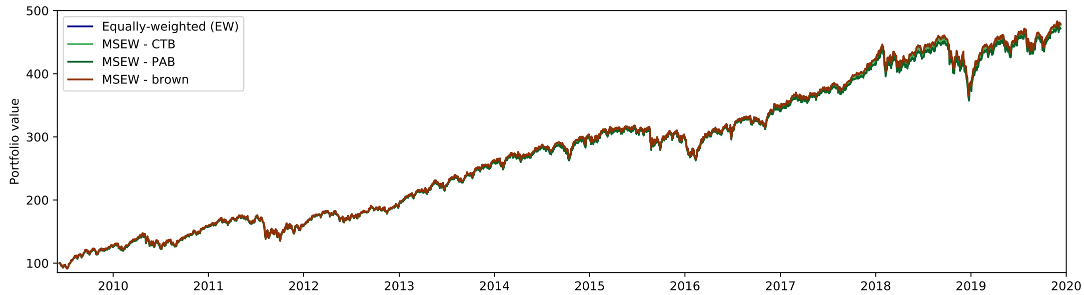
Table 11 evaluates performance and risk measures for each strategy. The unconstrained minimum variance strategy prescribes to hold on average the most concentrated portfolios. GHG reductions lead for both the constrained and most similar minimum variance strategies to a lower degree of concentration compared to a GHG increase. The maximum drawdown incurred throughout the entire investment period is smallest (i.e. least severe) for the minimum variance strategy. Enforcing a GHG increase with respect to the minimum variance reference leads to larger drawdowns than enforcing GHG reductions, both for the constrained minimum variance strategies (MV- ...) and the highest similarity strategies (MSMV- ...). The latter holds for the equally-weighted based strategies as well, with the only difference that the unconstrained strategy (EW) now has a larger MDD than both green strategies. All GHG strategies, except for the



(a) Constrained minimum variance strategies.



(b) Highest similarity strategies w.r.t. the minimum variance reference strategy.



(c) Highest similarity strategies w.r.t. the equally-weighted reference strategy.

Figure 24: Cumulative returns of Russell 1000 strategies with GHG intensity requirements.

brown MSMV strategy, have an annualized return above the return of the minimum variance reference strategy. They all have a larger annualized volatility as well. On the other hand, including GHG constraints in the equally-weighted strategy results in higher returns and volatility only for the brown MSEW strategy, while the reverse holds for the green strategies. Combining risk and return in the Sortino ratio, we find that

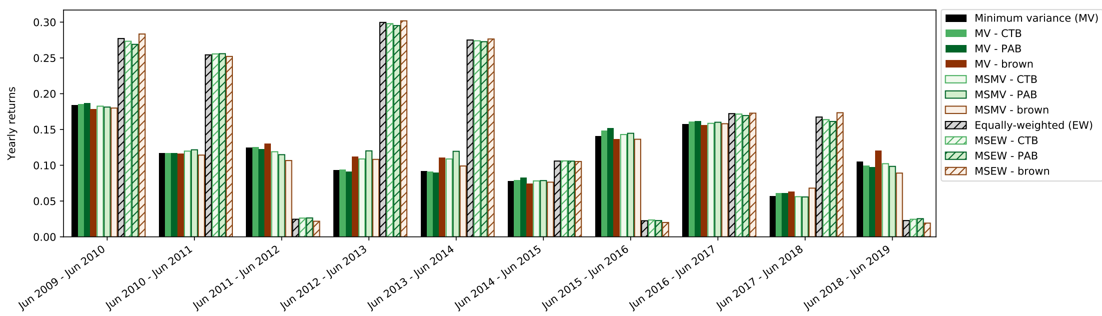


Figure 25: Yearly returns.

GHG reductions always lead to a Sortino ratio that is at least as high as that of the reference strategy. An increased GHG intensity leads to either a better (MV-B) or a worse (MSMV-B) Sortino ratio. The daily 95% VaR improves with respect to the minimum variance reference when GHG constraints are included, whereas the 99% VaR only improves for the constrained minimum variance strategies, and grows (in absolute sense) up to 8 basis points for the MSMV strategies. An increased GHG intensity with respect to the equally-weighted strategy leads to a worse VaR both on the 95% and 99% level, whereas GHG reductions alter the VaR with at most 1 basis point.

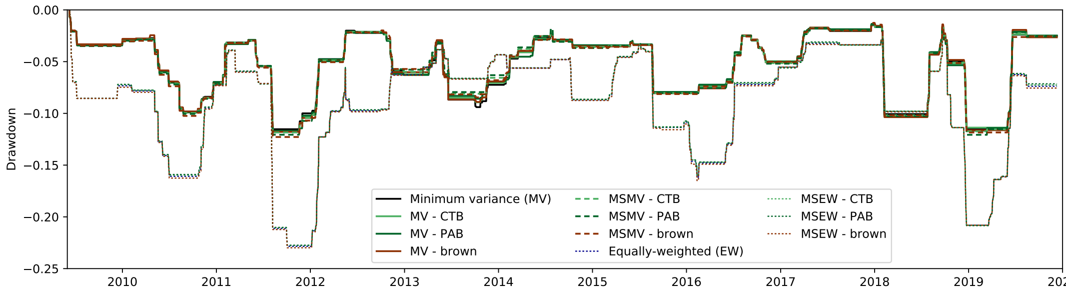
	MV	**MV-CTB**	**MV-PAB**	**MV-B**	**MSMV-CTB**	**MSMV-PAB**	**MSMV-B**
Average ENC	14.47	15.35	15.24	15.10	15.80	16.75	14.77
MDD	-11.54%	-11.69%	-11.68%	-11.79%	-11.84%	-12.07%	-12.28%
Annualized return	11.79%	11.96%	11.98%	12.31%	12.05%	12.22%	11.67%
Annualized volatility	10.10%	10.13%	10.13%	10.14%	10.18%	10.26%	10.25%
Sortino ratio	1.65	1.67	1.67	1.72	1.67	1.68	1.61
1-day $\text{VaR}_{0.95}$	-0.99%	-0.98%	-0.97%	-0.98%	-0.98%	-0.98%	-0.99%
1-day $\text{VaR}_{0.99}$	-1.66%	-1.68%	-1.68%	-1.67%	-1.70%	-1.74%	-1.71%
	EW	**MSEW-CTB**	**MSEW-PAB**	**MSEW-B**			
Average ENC	692.27	684.73	664.43	673.26			
MDD	-22.85%	-22.77%	-22.74%	-22.99%			
Annualized return	16.07%	16.03%	15.92%	16.09%			
Annualized volatility	16.25%	16.19%	16.16%	16.34%			
Sortino ratio	1.41	1.41	1.41	1.41			
1-day $\text{VaR}_{0.95}$	-1.59%	-1.58%	-1.59%	-1.61%			
1-day $\text{VaR}_{0.99}$	-2.92%	-2.93%	-2.92%	-2.98%			

Table 11: Risk and performance statistics of the Russell 1000 strategies with GHG intensity constraints (June 2009 - December 2019).

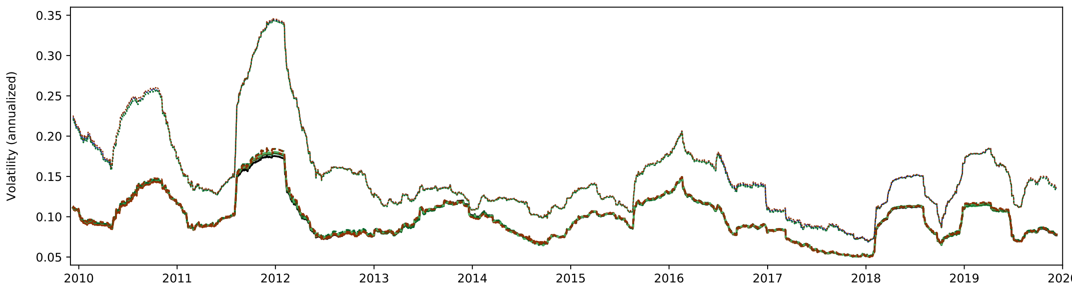
Figure 26 shows that both the six-months realized volatility and drawdown are not affected a lot by imposing GHG constraints on either the minimum variance portfolio or the equally-weighted portfolio. For instance, drawdowns are decreased by at most 0.99% with respect to both references. As opposed to the results for the European market, this holds for the entire investment period, i.e. from June 2009 until December 2019. Figure 27 quantifies the difference in volatility with respect to the reference universe as defined in Equation (36). We find that green constrained minimum variance strategies have an excess volatility of at most 36 and 35 basis points for respectively the CTB and PAB level of emission reduction. Green MSMV strategies are more risky and need up to respectively 52 and 88 basis points of additional volatility. All these maximum volatility differences stem from early 2012. In this period, the volatility itself took the highest value of 18% per annum. Figure 27c presents the excess volatility for the equally-weighted based strategies. We observe the same trend as in Figure 22c for the European analysis; GHG reductions result most of the time in a reduced volatility, while an increased GHG intensity comes with higher volatilities throughout the entire investment period.

5 Conclusion

In this paper, we discussed the impact of including environmental, social and governance (ESG) criteria in the allocation of equity portfolios. We performed an empirical analysis according to a standard mean-variance allocation framework, on which we imposed either positive (green) or negative (brown) sustainability constraints. Two different market sections were considered; a European universe represented by the assets in the STOXX Europe 600 index, and an American universe consisting of the assets in the Russell 1000 index.



(a) Six-months drawdown.

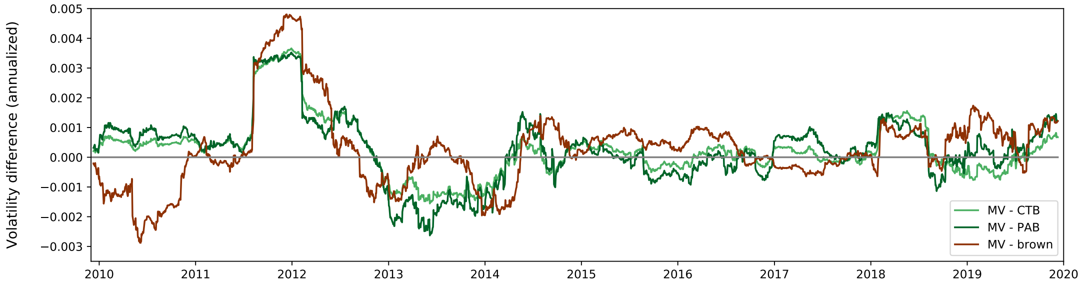


(b) Six-months realized volatility.

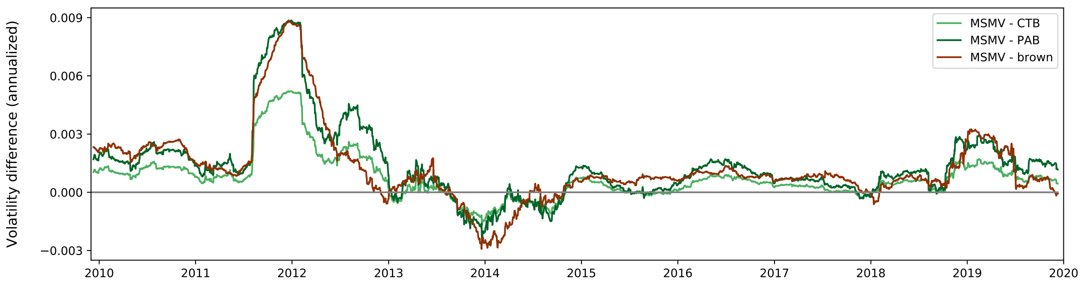
Figure 26: Risk characteristics of Russell 1000 strategies with GHG intensity requirements.

In the first part of the paper, we quantified the sustainability of a company by means of its ESG score published by the rating agency MSCI. For both universes, we found that brown strategies, i.e. strategies assigning more weight to companies with poor ESG scores, generated larger cumulative returns between December 2009 and December 2019. However, it turned out that their higher profits mainly originated from the returns realized in the first three years of the investment period. On the other hand, we found for both universes that green strategies, i.e. strategies assigning more weight to companies with high ESG scores, were performing better towards the end of the investment period. This tendency started early 2019 and mid 2017 for respectively the European and the American universe. Outside of these relatively short periods, we did not find clear-cut evidence for enhanced performance of portfolios with either high or low ESG scores. An intermezzo about ESG scores reported by Sustainalytics moreover illustrated that the results highly depend on the choice of rating agency. Hence, the impact of ESG rating constraints on a portfolio depends on which rating agency is used, as well as the specific market universe, the exact investment period, etc.

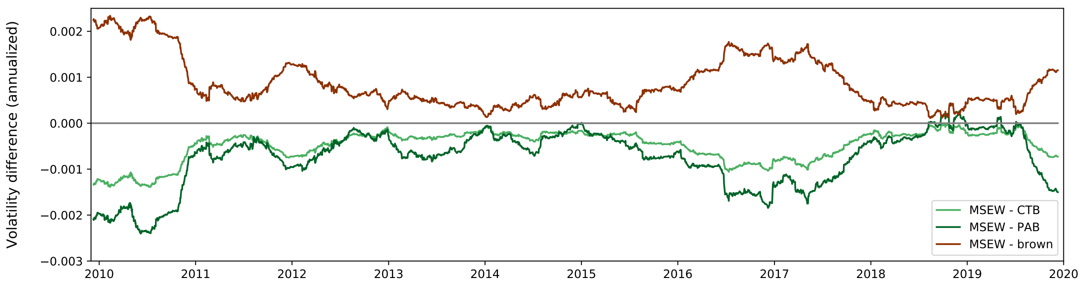
Secondly, we quantified the company's environmental sustainability according to its greenhouse gas (GHG) emission intensity. Motivated by the design of the recently proposed EU Climate Benchmarks, we studied how much impact GHG reductions of respectively 30% and 50% have on the performance and risk profile of a portfolio. In this analysis, we considered two reference portfolios; the minimum variance portfolio and the equally-weighted portfolio. We did not find an explicit relation between greenness of portfolios and their returns. Returns of GHG constrained strategies vary according to the type of strategy, asset universe and investment period. However, their overall annualized return always stays within 66 basis points from the annualized return of the reference strategy. The empirical analysis further showed that for both references an emission reduction does not necessarily lead to increased risk. Imposing emission reductions with respect to the equally-weighted portfolio even led to a reduced real-



(a) Constrained minimum variance strategies.



(b) Highest similarity strategies w.r.t. the minimum variance reference strategy.



(c) Highest similarity strategies w.r.t. the equally-weighted reference strategy.

Figure 27: Additional realized volatility of Russell 1000 strategies due to the inclusion of GHG intensity constraints.

ized volatility, and this for both the European and American markets throughout the entire investment period. Hence, based on historical evidence, a transition towards a green economy seems feasible without taking too much additional risk or losing potential returns.

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