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Constructing Investment Portfolios with Climate-Relevant Metrics: a multifaceted problem

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Ha DO
Amundi Technology
ha.do@amundi.com

Théo LE GUENEDAL
Amundi Technology
theo.leguenedal-ext@amundi.com

Meghna BHAUGEERUTTY
Amundi Investment Solutions
meghna.bhaugeerutty@amundi.com

Kevin ALINEJAD
Amundi Technology
kevin.alinejad@amundi.com

Skender BOUGHANMI
Amundi Technology
skender.boughanmi@amundi.com

Aaron MCDOUGALL
Amundi Investment Solutions
aaron.macdougall@amundi.com

Frédéric LEPETIT
Amundi Investment Institute
frederic.lepetit@amundi.com

Takaya SEKINE
Amundi Investment Institute
takaya.sekine@amundi.com

Abstract

The integration of climate-related signals within investment portfolios is becoming an increasingly mandatory requirement, as well as an expected practice, on the part of regulators and institutional investors respectively. In this paper, we illustrate the introduction of these metrics as optimization constraints, as outlined in Le Guenedal and Roncalli (2022). After recalling the diversity of climate-relevant metrics beyond carbon intensity, we integrate carbon historical trends, ambition reduction (derived from companies future targets) and run backtests of our novel multi-constraints optimization problem on the period from 2021 to 2024. We illustrate the impact of considering these metrics on performance and tracking error (T.E.). We show that the MSCI World Index theoretically tolerates a high level of integration of climate metrics with limited losses in performance or T.E. costs. Furthermore, we demonstrate that, in some cases, applying constraints of different climate aspects can yield better results than relying on a single, highly restrictive metric. Case studies show that portfolios combining moderate spot-decarbonization limits with stronger trend and ambition constraints can achieve comparable—or even superior—performance, depending on the period under consideration. This paper paves the way for the development of new methodologies for constructing aligned benchmarks.

Keywords: Climate change, optimization, portfolio alignment, benchmarked optimisation.

JEL classification: G11, G15, Q54.

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About the authors

Ha DO

Ha Do serves as a Quantitative Analyst at Amundi Technology, where his focus lies in deploying cutting-edge technologies within the Asset Management Industry. Previously, as a Quantitative Researcher at CPR AM, an Amundi subsidiary, he specialized in solvency modeling and machine learning. Mr. Do holds a Master's Degree in Actuarial Science from ISFA, University Lyon I in 2015, followed by a Master's Degree in Financial Engineering from University Paris Dauphine in 2017. His research focus lies at the convergence of factor investing, portfolio construction, and the application of machine learning methodologies for risk and investment strategies.

Théo LE GUENEDAL

Théo Le Guenedal is the Head of Prospective and Quantitative Solutions at the Innovation Lab of Amundi Technology. Prior to this, he worked in the Quantitative Research department of the Amundi Institute since 2018, starting with a project on the performance of ESG investing in the equity market. Since then, he has been involved in an extensive research project on incorporating ESG factors, alternative signals and climate risks into asset allocation strategies. In 2020, he co-authored a paper titled "Credit Risk Sensitivity to Carbon Price," which was awarded the GRASFI Best Paper Prize for Research on Climate Finance, a prestigious honor sponsored by Imperial College London. He also made significant contributions to the academic field of physical risk assessment by developing the Tropical Cyclone Generation Algorithm. Théo completed his Ph.D. thesis, "Financial Modeling of Climate-related Risks," in Applied Mathematics at the Institut Polytechnique in December 2023, covering both transition and physical risks. Recently, he has focused on integrating advanced climate metrics, stress tests, and analytics into investment tools at Amundi Technology's Innovation Lab.

Meghna BHAUGEERUTTY

Meghna Bhaugeerutty is a Quantitative Researcher within the Environmental Quant Solutions team of Amundi Investment Solutions since November 2024. Currently pursuing a Ph.D in Economics at Université Paris Dauphine - PSL, her research topics focus on the biases in Net Zero investing, portfolio decarbonisation, and physical risks in the financial industry. Meghna graduated from a Master's in Economic and Financial Engineering - Quantitative Finance from Université Paris Dauphine - PSL. Prior to joining Amundi, she worked as Quantitative Analyst on climate topics at Société Générale, namely modelling carbon trends.

Kevin ALINEJAD

Kevin Alinejad joined Amundi Technology's Innovation Lab in February 2024 to work on the Optimization of Investment Portfolios with Climate-Relevant Metrics, adopting a Multi-Objective perspective. This engagement is part of his Gap Year from September 2023 to June 2024. Prior to his tenure at Amundi, Kevin was a Data Scientist at Crédit Agricole. Kevin is currently a student at Télécom SudParis, a renowned engineering school, where he has pursued an extensive curriculum in Statistics & Probability, Optimization, Partial Differential Equations (PDE) and integration, Machine Learning, and Computer Science. He began his Master of Engineering program at Télécom SudParis in 2021 and plans to specialize in Mathematics and Data Science during his final year. Alongside his engineering studies, Kevin aims to complete a concurrent Master's degree with a focus on Mathematics.

Skender BOUGHANMI

Skender Boughanmi holds an MSc in International Finance from EDHEC Business School and specializes in Quantitative Research and Development. He began his career at the Innovation Lab in Dublin as a VIE in 2023, developing advanced analytical tools for portfolio managers. He later joined the London Office, contributing to the development of data-driven investment platforms and portfolio optimization tools for the Fixed-Income Team. His research focuses on big data analytics and quantitative modeling, including the development of the PM's Investment Cockpit, a data-driven decision-support system for portfolio managers. He has worked on developing robust data pipelines and implementing a multi-factor model for comprehensive factor exposure analysis at the fund level. Additionally, his work integrates climate constraints into portfolio optimization, aligning investment strategies with sustainability objectives while maintaining risk-adjusted returns.

Aaron MCDOUGALL

Aaron is the Head of Climate in Amundi's ESG Research & Engagement team. His work includes development of policy and frameworks to assess the climate performance of issuers within Amundi's investment universe, integrating climate costs into valuation models, and advising on climate and transition product innovation. Externally, Aaron is a core member of EC DG FISMA's Climate Benchmark developer community, contributed to the UK Transition Plan Taskforce, holds working group positions within the IIGCC and IEA, and leads CA100+ engagements on several major US firms. Aaron is an alumnus of Newcastle University, Strathclyde University, and University College Dublin, where he worked on the GreenWatch project with the Technical Expert Group of the European Commission's Platform on Sustainable Finance.

Fréréric LEPETIT

Frédéric Lepetit is Head of Equity Quant Portfolio Strategy within Amundi Institute. He joined Société Générale Asset Management in 2006 as quantitative analyst on the Equity side and expanded the scope of his activity to the volatility asset class area after the SGAM-CAAM merge in 2010. His areas of research cover ESG and factor investing. Prior to joining Amundi, he was consultant to French leading Asset Management companies at FactSet Research Systems from 1999 to 2006. Mr Lepetit holds a degree in economy and asset management from La Sorbonne University (1998).

Takaya SEKINE

Takaya Sekine, CFA is the Deputy Head of Quant Portfolio Strategy within Amundi Investment Institute (formerly known as the Quantitative Research Team of Amundi). In this role, he works on the practical implementation of quant research, artificial intelligence and alternative data for investment strategies. He joined Amundi in 2000 and is in his current position since July 2018. Prior to that, he was Deputy CIO at Amundi Japan (between 2011 and 2018) with a focus on global quantitative strategies, Head of Index and Multi-Strategies at Amundi Japan (between 2010 and 2011), Fund Manager (between 2007 and 2010) and Financial Engineer (between 2001 and 2007). He has been involved in macro and policy related investment strategies for both retail and institutional clients. Takaya began his career as an IT Manager at Amundi Japan's predecessor company (between 2000 and 2001). Takaya is a CFA charterholder since 2005. He received the Ingénieur Civil des Mines degree from Ecole des Mines de Nancy in 2000.

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1 Introduction

Since Mark Carney (2015)'s seminal speech, climate risk has become a critical factor in the financial industry and in asset management, in particular due to policies such as those necessary to follow the 2015 Paris Agreement. Thus, regulators and central bankers - in Europe and in Asia especially - have required that financial institutions establish stress-testing frameworks to measure the extent of their exposure to projected transition and physical risks, developing methodologies and publishing explicit requirements (Basel Committee on Banking Supervision, 2021; Berenguer *et al.*, 2020; ESMA, 2022; Feridun & Güngör, 2020; Hosseini *et al.*, 2022).

The integration of climate-related metrics is changing the traditional frameworks for both passive and active investors. Whether the aim is improving risk-return profiles or actively driving investments to support a more sustainable future, climate finance must now transition from the realm of academia to that of operational practice. Integrating climate-related signals into investment portfolios is becoming a critical consideration, driven both by regulatory requirements and demands from institutional investors. This integration process begins at the security level, where a comprehensive set of climate-related data metrics must be incorporated to accurately assess each issuer's environmental impact.

The initial step is therefore to integrate the multifaceted information that reflects the environmental impacts of the financed activity at the level of financial securities. It is imperative that a range of climate metrics, encompassing carbon footprint, carbon intensity and various scope emissions, are incorporated into the construction of the portfolio. Each issuer's underlying activity implies carbon greenhouse gas emissions. By dividing these emissions by revenues or other production metrics, the carbon intensity of the company can be readily deduced. An increasing number of companies report forward-looking carbon reduction targets and describe climate ambition plans in sustainability reports and regulatory reporting requirements (such as SFDR[1]). In addition, these metrics vary over time, which allows one to track the dynamic of carbon emissions and disclosure. Some additional information such as green (electricity, clean tech. etc.) revenues, European Taxonomy alignment (for revenues, operating and capital expenditure), or capital expenditures can be used when available.[2]

The second step is to develop more advanced and homogeneous harmonized risk metrics (Bouchet & Le Guenedal, 2020; Desnos *et al.*, 2023; Le Guenedal *et al.*, 2022; Roncalli *et al.*, 2020). For example, we can measure the change in credit risk due to the introduction of a carbon tax (Aiello & Angelico, 2023; Bouchet & Le Guenedal, 2020) or decarbonization in 2030 according to the setting of the target or the continuation of the current emission trend (Le Guenedal *et al.*, 2022). One could also wonder what a transition scenario (such as the Net Zero 2050 or Delayed 2°C) mean on a company's business (Le Guenedal *et al.*, 2023; van Benthem *et al.*, 2022), or what would be the distribution of risk accounting for carbon price and pass-through uncertainty (Desnos *et al.*, 2023).

The last step is simply to integrate this set of signals in the portfolio management process and investment strategies. Essentially, traditional portfolio optimization focuses solely

[1]SFDR (Sustainable Finance Disclosure Regulation) is an EU regulation aimed at increasing transparency in sustainable investments and preventing greenwashing in financial markets.

[2]For example, in Bhaugeerutty (forthcoming).

on risk and return, but some investors also consider non-financial goals like sustainability. For example, Le Guenedal and Roncalli (2022) compare portfolio decarbonization; reducing carbon emissions or intensity of a portfolio relative to a benchmark, with portfolio alignment which consists in a dynamic strategy to comply with climate policies, such as Paris-Aligned benchmarks (PAB) or Net Zero emission scenarios. It shows that portfolio alignment is more complex than decarbonization, especially when considering scope 3 emissions and issuer-specific carbon trajectories. Anquetin *et al.* (2022) also present the portfolio optimisation problem when all scopes of carbon emissions are taken in consideration.

In this paper, we focus further on the multidimensional aspect of portfolio management, including climate-related constraints (Ang *et al.*, 2024; Sandberg *et al.*, 2009; Xidonas & Essner, 2024). In particular, we reiterate the large and mature literature on both climate-relevant metrics (Bouchet & Le Guenedal, 2020; Desnos *et al.*, 2023; Fiedler *et al.*, 2021; Le Guenedal *et al.*, 2022; Roncalli *et al.*, 2020), and advanced portfolio optimization (ApS, 2024; Domahidi *et al.*, 2013). Many papers focus on the integration of extra-financial constraints for socially responsible investments (SRI) within the portfolio optimization problem (Ballestero *et al.*, 2012; Bender *et al.*, 2020; Bilbao-Terol *et al.*, 2012; Blitz *et al.*, 2024; Boudt *et al.*, 2013; M. Chen & Mussalli, 2020; Khan *et al.*, 2020; Varmaz *et al.*, 2024).

In the SRI space which generally uses Environmental, Social and Governance (ESG) metrics, we propose to focus on climate-related quantitative signals (as opposed to ESG scores or ratings) and illustrate that even this subtopic is subject to high dimensionality. This diversity of metrics is usually handled by aggregating the information in a single score. For example, historical carbon trend and carbon reduction target can be mixed to produce and 'implied temperature rating' (ITR). Instead, in the spirit of Blitz *et al.* (2024) and Garcia-Bernabeu *et al.* (2024), we consider several objectives and constraints to increase the sustainability of optimized portfolios. Indeed, building on the large literature available on multi-objective optimization and multi-dimensional efficient frontier surface (Bilbao-Terol *et al.*, 2012; Gintschel & Scherer, 2004), Blitz *et al.* (2024) extend this approach to mean-variance-sustainability optimization and show that multi-objective optimization is ex-ante Pareto-optimal, and highlight conditions where multi-objective optimization outperforms the traditional single objective method with added sustainability constraints. We confirm these results for Net-zero applications. Our methodology aims at integrating carbon constraints in an efficient manner in the portfolio optimization problem. Unlike seemingly similar papers (Zheng *et al.*, 2023), our problem can handle large scale optimization with a large number of assets, which is demonstrated through a study on indices; Pokou *et al.* (2024) and Xidonas and Essner (2024) propose an analogous research on indices.

The paper is structured as follows. Section 2 briefly summarizes a set of quantitative climate-relevant metrics available to perform such an optimization exercise. It focuses on approaches with published methodologies, but there are other commercial solutions.[3] In Section 3, we reiterate the formulation of optimization problems and provide some illustrative examples. Section 4 discusses the construction and generalization of this tool and provides concluding remarks.

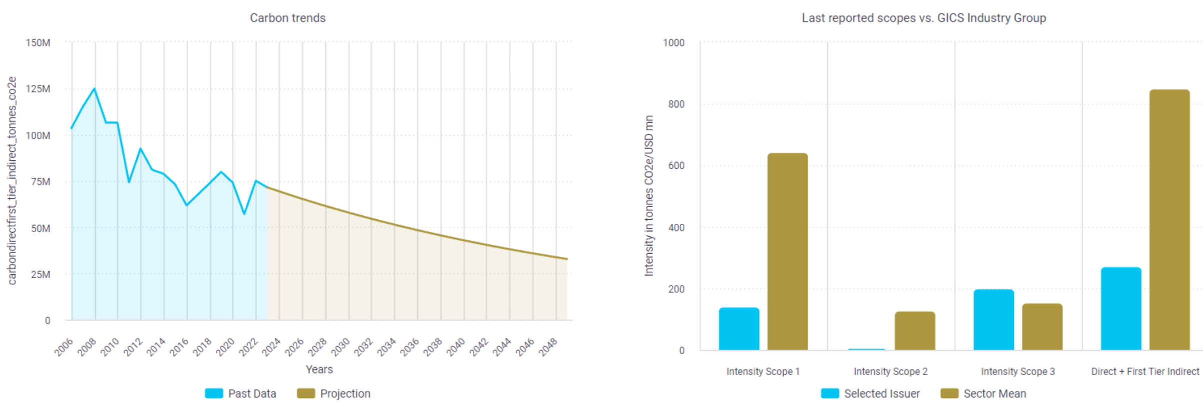
[3] For example, the climate VaR of MSCI, etc.

2 From raw data to climate risk metrics

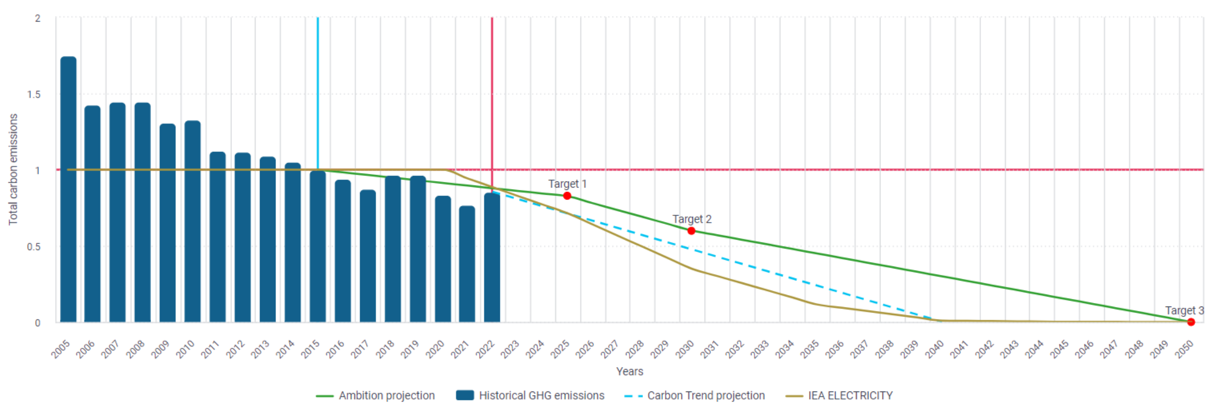
2.1 Climate-relevant data

Besides the concept of ESG, which encompasses a wide range of dimensions, this study focuses on the environmental characteristics of issuers, which vary significantly. The key metrics include absolute greenhouse gas emissions and carbon intensity, both of which are subject to temporal fluctuations (c.f. Figure 1a). Increasingly, issuers are also setting and reporting on specific carbon reduction targets, which provide forward-looking insights into their environmental strategies and commitments (c.f. Figure 1b).

Figure 1: Example of raw data visualization for an issuer



(a) Issuer carbon trend and intensity vs. Sector Average



(b) Issuer Carbon Ambition

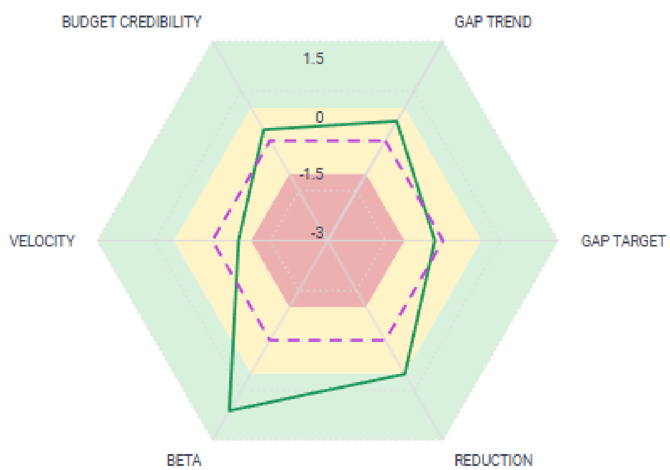
Source: Alto Climate, Trucost

Beyond direct emissions data, additional variables can enhance the climate profile assessment of each issuer. These include revenues from green activities, such as electricity generation from renewable sources and clean technology operations. The European Taxonomy for Sustainable Activities also offers a structured framework for classifying and comparing the sustainability of investments, thus encouraging transparency and uniformity in reporting practices. Furthermore, capital expenditures related to environmental sustainability are pivotal. These expenditures, often outlined in corporate sustainability reports, indicate the issuer's commitment to reducing environmental impact and transitioning towards more sustainable operations. Incorporating these expenditures into portfolio analysis can provide a more comprehensive view of an issuer's long-term sustainability trajectory. The aforementioned raw metrics are presented in first section of the Table 1.

2.2 Advanced Alignment and Climate-related risk metrics

To effectively integrate diverse climate signals into investment portfolios, quantitative frameworks that can handle multiple dimensions of climate-related data must be employed. This process involves the retrieval and analysis of historical emissions data as well as the evaluation of the potential impact of issuers' future commitments and green investments. The objective is to construct portfolios that align with climate objectives and adapt dynamically to evolving environmental data and regulatory landscapes. This integration addresses regulatory and client demands, positioning portfolios to potentially benefit from the transition to a low-carbon economy, thereby aligning financial performance with long-term sustainability goals.

Figure 2: Example of PAC-Radar (sector neutral z-score) illustrating some NZE metrics



Note: the dotted purple line represents the sector level and the green line is the issuer level. The red center section is associated with poor performance on the corresponding pillar while the green area is for best in class.
Source: Alto Climate

Subsequently, the raw information is harmonized to facilitate its integration into portfolio allocation. The paper uses the method presented in Le Guenedal *et al.* (2022) for this purpose. For instance, Figure 1a displays the 10-year logarithmic trend of Direct + First tier

Table 1: Quantitative Climate Metrics

Metric	**Definition**
Greenhouse Gas Emissions ($\mathcal{CE}_i$)	Total quantity of greenhouse gases emitted by the issuer, typically measured in equivalent tons of carbon dioxide (CO_2e).
- *Absolute Scope 1*	*Direct emissions*
- *Absolute Scope 2*	*Energy related indirect emissions*
- *Absolute Scope 3*	*Other upstream and downstream indirect emissions*
Carbon Intensity ($\mathcal{CI}$)*	The amount of carbon emissions per unit of output or economic value, allowing comparison across companies of different sizes and sectors.
Reduction Targets ($\mathcal{R}$)	Goals set by issuers to reduce their carbon footprint over a specified timeframe, indicative of their commitment to achieving lower emissions.
Green Revenues	Revenue derived from environmentally friendly products and services, such as renewable energy or clean technologies.
Fossil Fuel Revenues	Revenue derived from fossil fuel and non-renewable sources
European Taxonomy	A classification system established by the European Union to facilitate sustainable investment by defining which economic activities can be considered environmentally sustainable.
Reserves and energy mix	Amount of potential future emissions owned by companies and mix of resources used to produced the energy (for Energy and fossil-fuel companies)
Capital Expenditures on Sustainability	Investments made by a company to support sustainable practices, including spending on environmental technology and processes to reduce environmental impact.
Carbon transition pathway and alignment (PAC metrics)	Dynamic extension of carbon emissions, including reduction scenarios and company-specific trajectories. (Le Guenedal *et al.*, 2022) - see Table 2
Transition risk	Financial risk associated with carbon prices and sensitivity of asset prices to carbon risk factors.
- *Scenario-based Probability of Default and Spread*	*Credit risk sensitivity to carbon price* (Bouchet & Le Guenedal, 2022; Bouchet & Le Guenedal, 2020; Le Guenedal *et al.*, 2023)
- *Carbon Beta*	*Exposure of the stock to Brown-minus green (BMG) risk factor* (Roncalli *et al.*, 2020, 2021)
- *Climate transition VaR*	*Monte-Carlo approach on transition shock uncertainties* (Desnos *et al.*, 2023)
- *Scenario-based DFC ratio*	*Risk premia associated with shift in market pricing from baseline to transition scenario* (Le Guenedal *et al.*, 2023)
Climate physical risk (with *physical VaR*)	Financial losses resulting from climate change, including droughts, floods, and storms

*Carbon intensity are differentiated by scopes as well.

indirect emissions for a sample portfolio. This metric can be adapted by users in accordance with investment objectives. Table 2 presents detailed advanced metrics for an issuer compared to its sectoral average. Additionally, a transition (Desnos *et al.*, 2023) and physical Value-at-Risk (de Maximy *et al.*, 2024), carbon beta (Görgen *et al.*, 2020; Roncalli *et al.*, 2020, 2021), and advanced DCF and excess spread top-down measures build on scenarios designed with the EPPA model (Le Guenedal *et al.*, 2023, 2025) are also integrated.[4] All these *risk* metrics are available and may be used in portfolio construction.

In this paper, we illustrate a first case study using carbon trend and ambition metrics for *portfolio alignment* (PAC metric, Le Guenedal *et al.*, 2022).[5] Figure 2 displays a radar that illustrates different key metrics for a given company in the Energy GICS sector. In this example, we can see that this company has historical trend, reduction slope and achieved reduction above its sector. The participation of company to the reduction effort is therefore positive. In terms of target the company is more conservative with a target budget[6] slightly below average. The company's credibility appears to be positive. Since its initial target setting, it has demonstrated a reduction that is aligned with the engagements.[7] Table 2 presents some key metrics that can be used in portfolio optimization in the context of alignment with simplified definition.

Table 2: Example of NZE metrics from PAC model (Le Guenedal *et al.*, 2023) for an issuer in the Energy Sector

Pillar	Metric	Definition	Issuer	Sector
Participation	Gap	The gap between the carbon trend emissions and the NZE scenario in 2050	0 KtCO2e	-61.85 KtCO2e
	Reduction	Remaining GHG emissions, following the trend, in 2050	0.0 %	35.07 %
	Trend	The beta coefficient of the trend	-0.06	0.02
	Trend	The coefficient of determination of the trend R^2	89.0 %	40.45 %
	Trend	The emissions in 2025	27.7 MtCO2e	21.08 MtCO2e
	Velocity	The velocity of emissions reduction	0.001	-0.0014
Ambition	BA	The carbon targets budget	201.48 MtCO2e	42.81 MtCO2e
	Gap	The gap between the carbon targets emissions and the NZE scenario in 2050	0 KtCO2e	-61.85 KtCO2e
Credibility	BC	The diffrence between the ambition budget and the trend budget	-9.97 MtCO2e	41.04 MtCO2e
	Gap	The normalized difference between the ambition gap and the trend gap)	0 MtCO2e	35.22 MtCO2e
	Slope NZE	The normalized beta coefficient of emissions reduction to respect the NZE scenario	-0.03	-0.03
	Slope NZE	The normalized beta coefficient of emissions reduction to respect the NZE scenario divided by the beta of the trend	0.5	-1.44

Source: Alto Climate, method based on Le Guenedal *et al.* (2023)

[4]EPPA is a general computable equilibrium model developed by the MIT Center for Sustainability Science and Strategy (Y.-H. H. Chen *et al.*, 2022).

[5]We keep the integration of risk metrics (VaR, DCF, etc.) for further research.

[6]Corresponds to the difference between target setting and IEA requirements, see Le Guenedal *et al.* (2022) for more information on the definition of the metrics.

[7]Note that these metrics are highly parametric. For example, the value depends on the consideration of Scope 1, 2 and 3 in the construction of the trends.

2.3 Focus on Carbon Intensity, Participation and Ambition

As discussed, both Carbon Emissions and Intensity are raw metrics of the issuer, which offer a snapshot of past environmental performance. On the positive side, carbon emissions and intensity data provide a clear and quantifiable measure of an issuer's current environmental impact, allowing for easy comparison across different issuers. These metrics are widely recognized and standardized, making them valuable for benchmarking purposes. Additionally, they can help identify the most significant polluters, guiding efforts to reduce overall emissions.[8]

However, there are also drawbacks: first, these metrics are backward-looking because they do not account for future environmental strategies and commitments, limiting their relevance for long-term investment decisions. Second, they can be influenced by short-term variations that may not accurately reflect an issuer's overall sustainability trajectory. Moreover, they do not capture the broader environmental impacts of an issuer's operations, such as biodiversity loss or water use. Consequently, relying solely on these metrics may provide an incomplete picture of an issuer's environmental performance. Therefore, it is essential to consider additional forward-looking and comprehensive metrics which can offer a more holistic assessment of an issuer's commitment to sustainability, and its alignment with long-term climate goals.

Hence, these two illustrative metrics come immediately to mind: *i) Carbon Trend* and *ii) Carbon Ambition*.[9] Carbon Trend refers to the historical analysis and extrapolation of a company's carbon emissions over a specified period, reflecting the trajectory of their environmental impact. The metric provides valuable insights into the evolution of a company's carbon footprint over time, offering a clear picture of past performance and potential future trends from an external analysis perspective. The data is computed based on Trucost historical data, from 2012 to 2023.[10] Conversely, Carbon Ambition metric aims to give more weight to issuers that have announced higher carbon reduction ambition in the future, meaning a higher engagement in reducing their greenhouse gases emissions (expressed in carbon equivalent) by a target horizon. The level of disclosed ambitions is the emissions in 2030, of the projected implied trajectory defined in Le Guenedal *et al.* (2022). It encompasses targets set by management, including activities such as carbon reduction plans, investments in green technologies, and timelines for achieving carbon neutrality. While the carbon trend anticipates changes in emission activities, carbon ambition reflects the company's future sustainability goals. Both metrics are forward-looking: the carbon trend relies on data-driven forecasts, and carbon ambition outlines strategic plans.

Data Analysis Given the markedly skewed distribution of Carbon Intensity, a logarithmic transformation was implemented on this variable to enhance interpretability. Tables 3 and 4 present the descriptive statistics of the selected metrics, while Figure 3 displays the pair

[8] The metrics are all extracted from Alto Climate, and follow the definitions presented in Le Guenedal *et al.* (2022). In particular, we reiterate the definitions of the metrics used in this exercice in the Appendix A.1.

[9] The definition of the metrics are reiterated in the Appendix A.1.

[10] The carbon trend is however sensitive to the fitting period chosen. This parameter may depend on the client mandate.

plot. The Carbon Trend is primarily concentrated around 0, exhibiting minimal variation (standard deviation = 0.15, quantile 25th = -0.04, quantile 75th= 0.08) along with some very extreme values. Conversely, the Carbon Ambition metric, aside from a large portion of null values in the sample, is spread over a wide range with a median value of 30%. In the overall dataset, the correlation between the three metrics is relatively weak. However, within sectors, we observe a negative correlation between Carbon Trend and Ambition: this indicates that companies with a positive trend in carbon emission usually don't have high ambition to reduce them.[11]

Table 3: Summary Statistics for log CI direct FT*, Carbon Trend, and Carbon Ambition

	Mean	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
log Carbon Intensity	4.1341	1.6412	0.5464	2.9996	4.0435	5.171	9.0411
Carbon Trend	0.0323	0.1460	-0.9300	-0.0400	0.0100	0.080	1.6500
Carbon Ambition	29.1605	29.8915	0.0000	0.0000	30.0000	50.000	122.5200

* log CI direct represents the logarithm of Carbon direct and first tier indirect emission intensity

Table 4: Carbon Data Correlation

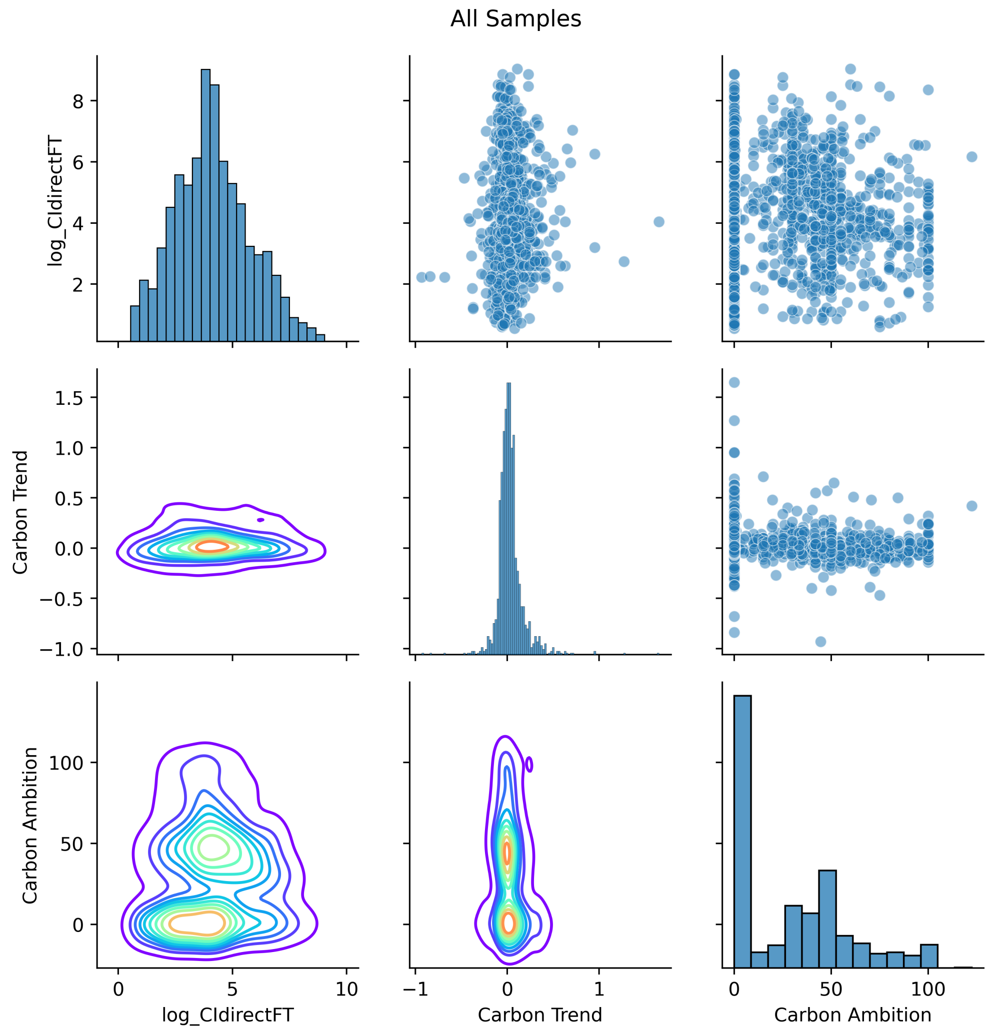
	Cb. Int.* x Trend	**Cb. Int. x Ambition**	**Cb. Trend x Ambition**
All Samples	6.0%	3.9%	-13.4%
Energy	3.2%	-12.11%	-28.00%
Utilities	47.0%	0.76%	-10.2%
Comm. Serv.	22.5%	22.5%	-20.0%
Health Care	4.3%	3.0%	-24.7%
Real Estate	47.8%	1.3%	19.35%
Info. Tech.	-10.7%	21.5%	-35.0%
Financials	15.5%	4.6%	-11.5%
Cons. Staples	-8.1%	-12.0%	-31.2%
Materials	10.0%	-4.3%	0.0%
Cons. Disc.	-2.2%	-12.5%	-5.7%
Industrials	15.7%	-9.0%	-13.8%

* Cb.Int. is the log Carbon Intensity

Figure 3 presents a pairplot analysis of three key variables: the logarithm of Carbon direct and first-tier indirect emission intensity (hereafter referred to as log(CI)), Carbon Trend, and Carbon Ambition. The diagonal histograms indicate that both log(CI) and Carbon Ambition exhibit right-skewed distributions, suggesting a concentration of lower values with a tail extending towards higher values. In contrast, Carbon Trend displays a

[11] Detailed statistics and pair plots for the sectors can be found in the appendix.

Figure 3: Carbon Data Analysis



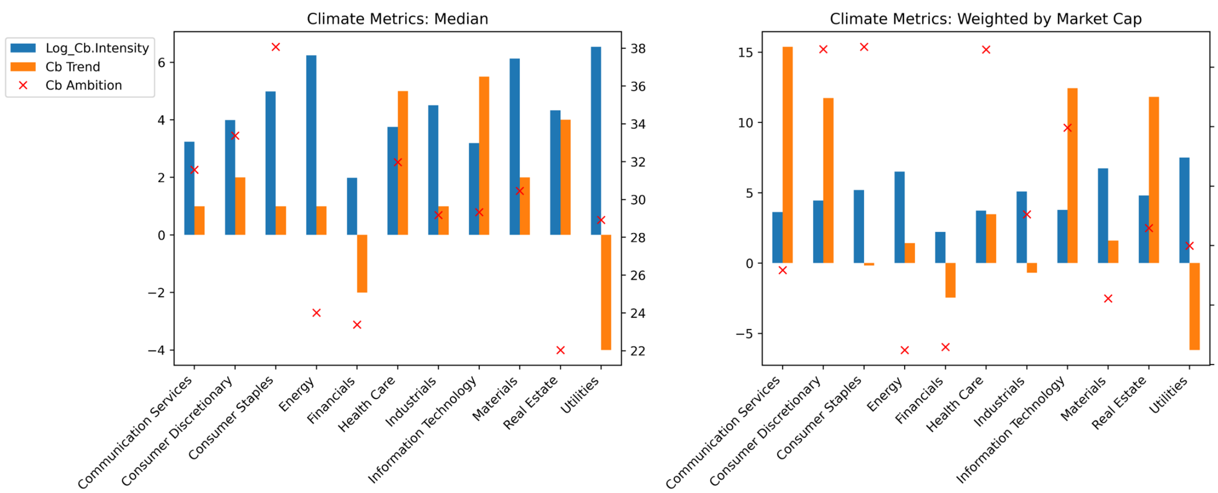
Note : log_CIdirectFT represents the logarithm of Carbon direct and first tier indirect emission intensity

more normal distribution across its range. The scatter plots reveal weak positive correlations among the variables, particularly between log(CI) and Carbon Trend, as well as between Carbon Trend and Carbon Ambition. The contour plots further illustrate the density of observations, indicating that lower values of Carbon Trend and Carbon Ambition are more prevalent. Collectively, these findings suggest that while there are some interrelationships among the variables, they are relatively weak and exhibit a degree of orthogonality. This orthogonality allows for the construction of a Green Signal comprising three dimensions that are conceptually related but not empirically correlated.

The Figure 4 illustrates the median and cap-weighted values of the three metrics by sector. The left y-axis represents the log Carbon Intensity and Carbon Trend, while the right y-axis corresponds to Carbon Ambition. If we focus on absolute carbon emissions, the Energy and Utility sectors would have been identified as the strongest contributors. While Energy has a positive trend, Utilities has the most significant negative carbon trend, by both median and cap-weighted measures. The discrepancy between the sector median and cap-weighted values of the Carbon Trend indicates that larger market players predominantly display a positive trend. Consequently, stricter control of the Carbon Trend would promote smaller companies (the size factor) and ones in the Utilities sector. The Financial sector demonstrates the lowest Carbon Intensity, both by median and cap-weighted measures, making it the first candidate to consider to add to the portfolio if no extra controls are applied.[12]

Figure 4: Carbon Data Analysis by Sector

Left: by median; Right: by weighted with Market Cap



3 Portfolio Construction with Climate Metrics

Integrating climate risk metrics into portfolio optimization has become essential in the context of sustainable and impact investing. Despite this integration theoretically aligning with traditional portfolio models, practical applications can significantly alter portfolio structures, particularly under stringent constraints such as those aimed at achieving net-zero carbon emissions. The most common way to control carbon or transition metrics is through constraints in the portfolio construction process. [13]

Notations Portfolio optimization traditionally relies on key inputs including the expected return vector μ, asset volatilities σ, and the correlation matrix ρ. From σ and ρ, the covariance matrix Σ is constructed, where $\Sigma_{i,j} = \rho_{i,j}\sigma_i\sigma_j$. Portfolio weights, represented by vector $x = (x_1, \ldots, x_n)$, enable the computation of the portfolio's expected and variance returns, where the expected return is $\mu(x) = x^\top \mu$ and the variance is $\sigma^2(x) = x^\top \Sigma x$. The portfolio's

[12] As Le Guenedal and Roncalli (2022) highlights, the complexity of the overall problem increases with the inclusion of Scope 3 (indirect emissions), as it further balances risk metrics across sectors.

[13] We reiterate the optimization problem from Le Guenedal and Roncalli (2022) in the Appendix A.3.

risk is quantified by its volatility, $\sigma(x)$. When incorporating climate-related risks, an additional metric, $\mathcal{C}_i$, which quantifies the climate risk associated with asset i^{th}, is integrated to control the characteristics of the final portfolio.

Data The benchmark employed in this analysis is derived from the composition of the MSCI World Equity Index (Source: MSCI, Factset). We incorporate data on Carbon Absolute and Intensity for Scope 1, Scope 2, as well as Direct and Indirect emissions, sourced from Trucost, along with Carbon Targets reported directly by the Carbon Disclosure Project (CDP). To ensure comprehensive carbon data availability for each company, our benchmark comprises more than 95% stocks from the index[14], resulting in a loss situation between 5-10% of the MSCI World Index composition. The calculation of the Carbon Trend follows the methodology outlined in Le Guenedal *et al.* (2022). The analyses conducted pertain to both Carbon Intensity and Carbon Emissions, yielding comparable results; consequently, we present only the findings related to Carbon Intensity. Furthermore, we provide results for the calendar year 2023, noting that similar outcomes were observed for the calendar years 2020 to 2022.

Software The optimization exercises in this paper are conducted using Amolite: **Am**undi **O**ptimization **Lite** Version, an internal optimization library integrated into Alto Climate. Traditionnal controls, such as cardinality (number of holdings, trade, or 5/10/40 constraints), are also handled by Amolite.[15]

3.1 Green Trackers

As discussed in Section 2.3, since the selected metrics are weakly correlated, one may apply the traditional ranking (z-scoring) then average procedure to arrive at a composite “green” ranking. Therefore, a portfolio manager simply needs to include the higher green ranked assets without precisely monitoring the single metric exposure of the portfolio. In our example, the composite metric is defined as the weighted average of the metric rankings from the entire MSCI universe. On the one hand, this approach simplifies the multi-dimensional aspects of climate metrics, providing a more straightforward pathway for integrating green assets. On the other hand, however, this method bears similarities to the ESG composite metric that amalgamates different sub-categories at varying levels.

Problem Introduction The use of a composite score as a portfolio’s green exposure in portfolio construction can be expressed either as a “green signal” to maximize or as an extra constraint level to achieve. In this section, we consider the maximum signal given the benchmark’s Tracking Error (T.E.) budget problem. The idea is to find the greenest possible portfolio that closely tracks the benchmark, which we call a “green tracker”. The problem is formulated as:

$$x^* = \arg\max s^t x \quad \text{s.t}$$

[14] As of the time of writing, the MSCI World Index consists of 1,395 constituents.

[15] We reproduced some results from Le Guenedal and Roncalli (2022) using the same solver for robustness checks.

$$\sigma(x-b) = \sqrt{(x-b)^t \Sigma (x-b)} \leq ub_{te}; \quad x \in \Omega$$

where s is the green composite constraint, x, b are the portfolio and benchmark weights, $\sigma(x-b)$ is the ex-ante tracking error (T.E.) of the portfolio relative to the benchmark, Σ is the covariance matrix, ub_{te} is the ex-ante T.E. budget, Ω is the set of additional practical constraints to control other characteristics of the optimized portfolio. In this example, portfolio optimization is subject to the following constraints. First, all asset weights must be between the smallest weight of the benchmark and 3% [16], and the portfolio are fully invested.

$$bmk_{min} \leq x_i \leq 3\%, \quad \forall i. \quad \text{and} \quad \sum x_i = 1, \quad \forall i.$$

The portfolio's sector constraints, preventing excessive portfolio concentration in specific sectors, promoting diversification, forces the sector allocation to remain within ±3% of the benchmark allocation in each Global Industry Classification Standard (GICS) sector:

$$|\sum(x_i - b_i|_{i \in S})| \leq 3\%,$$

where S represents a given GICS sector. The bounds of the sector alignment constraint have been tested with alternative values of ±4% and ±5%, yielding similar results.[17] Finally, the weighted sum of individual asset betas must equal one, ensuring that the portfolio maintains a targeted market exposure: $\sum \beta_i x_i = 1$, where β_i represents the Capital Asset Pricing Model (CAPM) adjusted beta (daily 6-month estimate) of asset i relative to the benchmark. [18]
A *baseline tracker* is also calculated for the same set of constraints by solving:

$$x_0^* = \arg\min \sigma(x-b) \quad \text{given } x \in \Omega$$

without incorporating any green information. The T.E. archive is approximately 166.21 bps, serving as a lower bound for the T.E. budgets. Furthermore, to understand the characteristics of the "green tracker", the T.E. ex-ante budget ub_{te} varies from 200 bps to 500 bps. All portfolios are formed as of year end (e.g. 31/12/2023).

Efficient Frontier & Impact of Green Signals Figure 5 represents the evolution of the weight in the GICS sectors with respect to tracking error. To better illustrate the drift, the sector alignment constraints in this subsection were temporarily removed. The graph shows the sectoral composition of the efficient frontier portfolios, providing information on the changes in sector weights as constraints become more relaxed. The x-axis represents the tracking error in basis points, the left y-axis shows the weight percentage of each GICS sector, and the right y-axis indicates different levels of green signal. Each color in the stacked bar chart represents a different GICS sector. As anticipated, the share of polluting sectors decreases rapidly. For instance, starting from an T.E budget of 300 bps, no stocks from the Energy Sector and Consumer Staples remain. Our analysis reveals that the portfolio achieves a reasonably high green signal exposure, ranging from 0.65 to 0.75, with a T.E

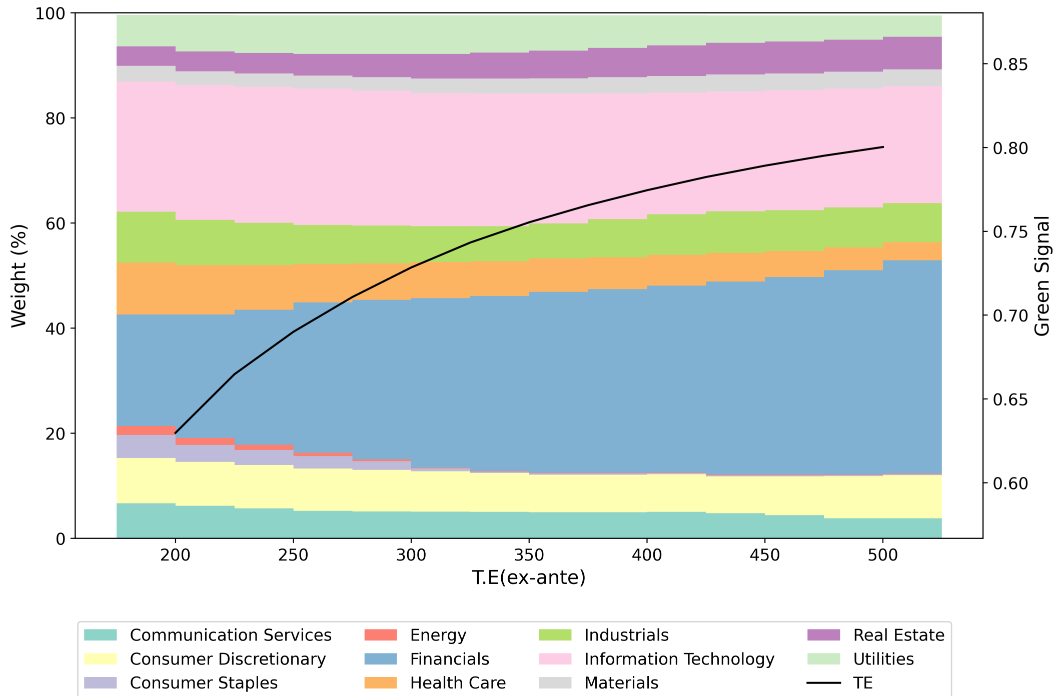
[16] The max weight of MSCI World varies from 2% to 5% in the period of 2019-2023

[17] Note that relaxing this constraint leads to an outperforming portfolio in the recent period due to a greater exposure to the financial and health care sectors.

[18] The adjustment is the shrinkage toward 1, following Vasicek (1973), Bloomberg: $\beta_{adj} = 0.67 * \beta_{ols} + 0.33 * 1$

budget of 175 to 300 bps, in comparison to a score of 0.5 for the benchmark and baseline tracker (table 14).The Table 5 report the contribution of companies to the green signal, by sector.

Figure 5: Efficient Frontier decomposed by sectors - without Sector Allocation Constraints



From the perspective of signal contribution, it is clear that the primary contributors are the Financial and Information Technology sectors.[19] Despite their small green contributions, sectors such as Materials and Real Estate are essential to accurately track the index. Following the T.E trace, their weights do not diminish as quickly as those of polluting sectors. Furthermore, there is potential to identify green companies within the Communication Services, Consumer Discretionary, Health Care, and Industrials sectors as their contributions are not benign. In summary, while the initial removal of sector alignment constraints highlights the rapid reduction of polluting sectors, maintaining these constraints still ensures high green signal exposure with broad sector representation. This exercise underscores the balance between achieving green objectives and maintaining a diversified portfolio.

Figure 6 presents the climate metrics of spot carbon intensity, carbon trend, and future reduction ambition. The number in parentheses represents the T.E ex-ante in basis points to the benchmark. Sectoral alignment constraints are included in these results. The x-axis displays the portfolio scenarios with increasing TE budget, while the right y-axis indicates

[19]Note that this is due to a focus on direct emission / intensity signals (as well as the leverage and relative weight of I.T. sector in benchmark composition which is notably higher than climate intensive ones). The impact of the inclusion of the green metric on optimized portfolio sectoral composition can be modified when considering indirect emission and supply chains. We keep this question for further research (Adenot *et al.*, 2022; Desnos *et al.*, 2023).

Table 5: Green Signal Contributions (%) by Sector and TE bugdet

	200	**225**	**250**	**275**	**300**	**325**	**350**	**375**
Comm. Serv.	5.44	5.04	4.67	4.38	4.33	4.36	4.38	4.37
Cons. Discr.	7.57	7.33	7.01	6.69	6.45	6.30	6.18	6.09
Cons. Staples	4.31	3.03	2.61	2.06	1.41	0.42	0.18	0.18
Energy	1.47	1.13	0.78	0.47	0.23	0.05	0.05	0.05
Financials	26.13	29.26	31.96	33.85	35.33	37.23	38.56	39.28
Health Care	10.44	9.21	8.00	7.48	7.20	6.78	6.44	6.04
Industrials	9.35	8.24	7.40	6.81	6.49	6.34	6.32	6.96
Info. Tech.	21.96	22.84	23.50	24.01	24.12	23.63	22.90	22.10
Materials	2.45	2.42	2.47	2.51	2.64	2.95	3.13	3.29
Real Estate	4.16	4.08	4.07	4.22	4.42	4.84	5.18	5.42
Utilities	6.71	7.42	7.52	7.51	7.38	7.09	6.68	6.21

the percentage of carbon spot reduction and carbon ambition (with a maximum value of 100%). The left y-axis represents the Carbon Trend computed on reported annual emissions over the last 10 years.The figure shows that along the tracking error (TE) budget path, both the Carbon Trend and Carbon Intensity Reduction improve monotonically. In contrast, Carbon Ambition plateaus beyond a budget of 300 bps, stabilizing at a relatively high level of 70% from a starting level of 50% - notably higher than the 75th percentile of 50% observed in the broader universe or the ambition score of 35% of the benchmark and the baseline. It means that it is easier to achieve the Carbon Ambition objective rather than the Carbon Trend and Carbon Intensity ones.

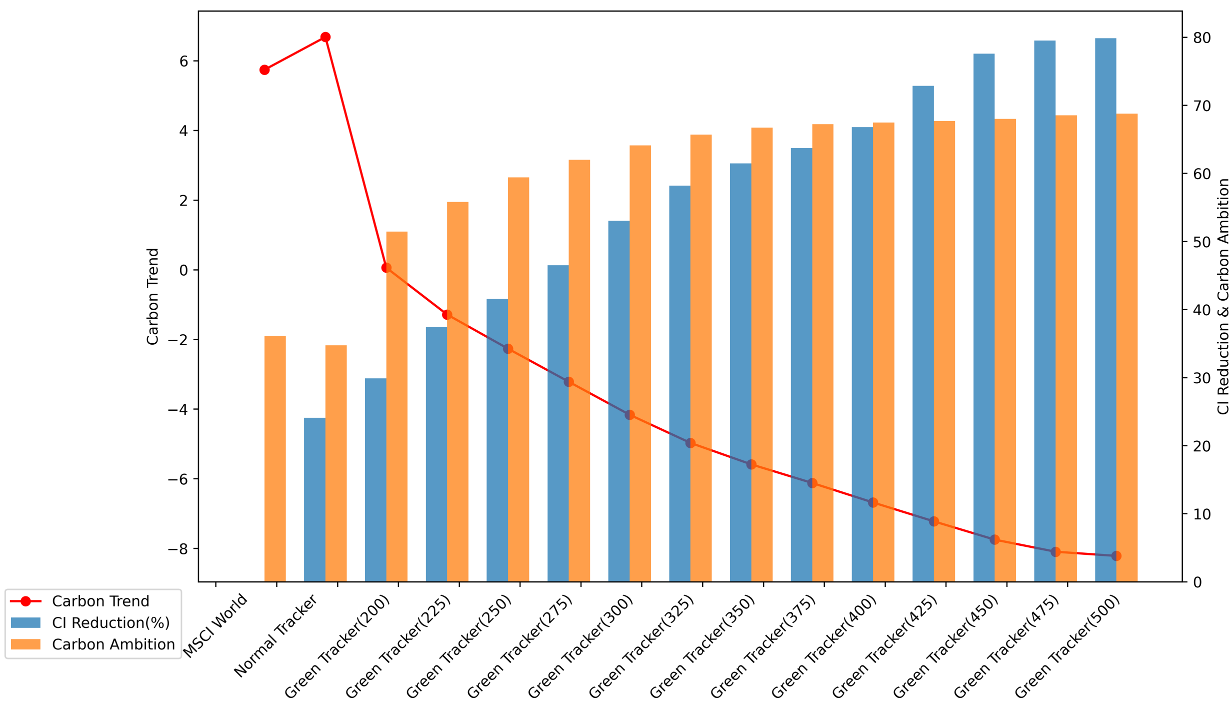
While the tracker is incrementally steered towards the "*green*" direction using a composite signal, the green trackers demonstrate substantial improvements in spot carbon intensity reduction, carbon trend, and higher future carbon reduction ambition compared to the baseline tracker. For example, a Green Tracker (250) achieves a -41.50% CI reduction with a -2.26 carbon trend and a 59.50% carbon ambition, in contrast to the +24.09%, 6.68, and 34.74% values of the baseline, respectively (which are close to those of the benchmark).

In Table 6, we present the T.E ex-post (in bps) of the green trackers compared to the baseline tracker, as well as the associated one way turnover. Our findings indicate despite the significant differences in structure, the overall green trackers only has relatively small increase in T.E, in comparison to the baseline tracker, e.g the Green Tracker with (ex-ante) budget of 200 attains only 240 bps of T.E. ex-post in next month, in comparison to a value of 196 bps of baseline Tracker, while its one way turnover is approximately 43%. We further observe that the green trackers exhibit a notable difference from the baseline tracker, as evidenced by a significant turnover rate, as well as the climate metrics, yet the trade-off of T.E ex-ante can be relatively small.

3.2 Benchmarked Portfolios with Climate Targets

Problem Introduction Experienced practitioners seeking to achieve precise control over various aspects of the climate issue may consider encoding this information into portfolio

Figure 6: Climate Metrics of Green Trackers



Note: The number in parentheses represents the T.E ex-ante to the benchmark

constraints with specific target levels. The conventional portfolio optimization model can be represented as follows:

$$x^*(\gamma) = \arg\min \frac{1}{2}(x-b)^t\Sigma(x-b) - \gamma\mu^t(x-b)$$

Given:

$$C(x,b) \leq u_C, \quad \forall C \in \mathcal{C}$$

where $C(x,b)$ represents the climate metric, potentially in relation to the portfolio and the benchmark, $\mathcal{C}$ denotes the set of climate constraints; and $x \in \Omega$, where Ω is the same as defined in Section 3.1. Note that, for the three selected metrics, the reduction of carbon emissions or carbon intensity can be performed in an absolute or relative manner (that is, versus a benchmark). It is observed that a straightforward formulation of carbon reduction may or may not be linear (see Le Guenedal and Roncalli, 2022 Section 2 for more details). Otherwise, the carbon trend and the carbon ambition are additive. To facilitate comparison with Section 3.1, the term μ in the objective function is ignored, resulting in a benchmarked portfolio problem with the target levels of the climate metrics.

Table 6: T.E. (ex-post, in bps) and Turnover(%) for given ex-ante budget

Tracker	T.E. (ex-post, in bps)				Turnover(%)
	1M	2M	3M	6M	
Baseline Trkr	195.96	225.73	214.97	197.99	x
Green(200)	239.42	282.53	262.67	248.15	42.85
Green(225)	280.72	315.81	297.52	278.36	53.35
Green(250)	303.43	338.19	326.47	303.46	59.96
Green(275)	316.16	358.30	356.74	332.06	64.47
Green(300)	345.22	381.72	386.67	360.62	67.69
Green(325)	382.61	410.51	412.23	385.32	70.03
Green(350)	414.72	436.80	438.55	410.91	72.41
Green(375)	438.57	459.74	462.72	432.45	75.08
Green(400)	459.14	479.49	486.32	454.20	78.17
Green(425)	483.62	508.13	514.77	478.12	80.51
Green(450)	504.74	536.21	542.78	500.97	83.02
Green(475)	525.34	564.73	571.92	523.47	85.40
Green(500)	547.07	594.23	598.24	543.41	86.16

Note: The number in parentheses represents the T.E ex-ante to the benchmark

Climate Constraints The sets of climate constraints are as follows:

$$\begin{cases} \sum x_i CI_i \leq (1-R)CI(b) \\ \sum x_i CT_i \leq ub_{CT} \\ \sum x_i CA_i \geq lb_{CA} \end{cases}$$

To study the impact of the Climate Metric target level, the reduction rate is set to $R = 0$ or 75%, and the targets:

$$ub_{CA} \in [0, 75], \quad lb_{CT} \in [0, -0.15]$$

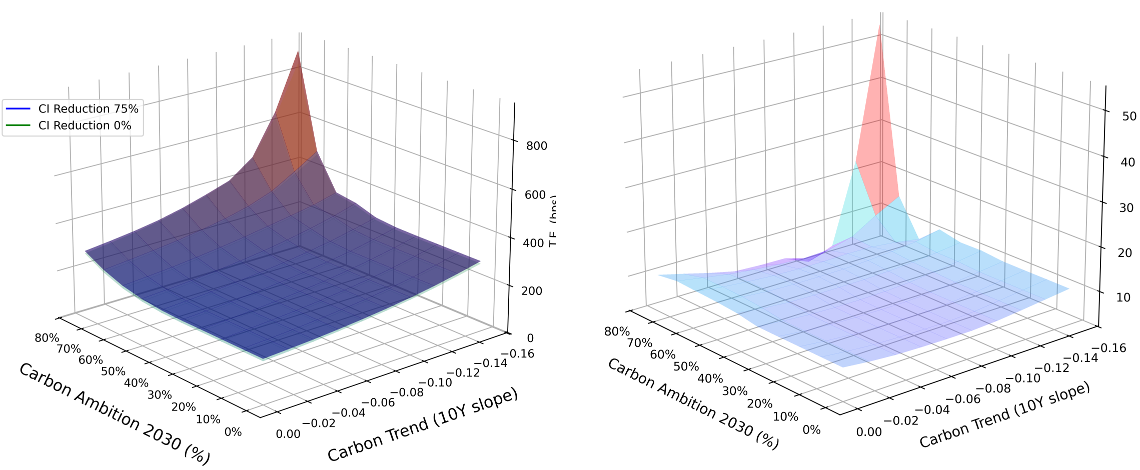
are varied. The Tracking Errors (T.E., ex-ante) of the green portfolios are then reported. In this exercise, the targets are pushed to a highest level possible [20] in comparison to the 3.1(e.g., a value of trend -15%, ambition of 75% compared to the highest value of -8.21% and 70% of the green trackers, respectively).

Impact of Carbon Constraints Figure 7a depicts the relationship between Carbon Reduction thresholds of 75% and 0% as a function of Carbon Trend, Carbon Ambition, and ex-ante Tracking Error (T.E.). It is noteworthy that the influence of Carbon Reduction on ex-ante T.E. is minimal when compared to an optimization scenario without any reduction, as evidenced by the proximity and frequent overlap of the two planes. Conversely, a pronounced effect emerges when considering the historical reduction efforts (Carbon Trend) and the commitment to reduction (Carbon Ambition) regarding corporate carbon emissions,

[20] where we still have feasible solution

which can bring the T.E. close to 900 bps. Figure 7b illustrates the difference between the two planes corresponding to a Carbon Intensity reduction level of 75% and that of 0%. The findings indicate a marginal increase of approximately 10 basis points in T.E. for portfolios with low levels of Carbon Ambition if they have a higher decarbonization rate. In contrast, the implications of implementing a high Carbon Intensity Reduction rate or a high Carbon Ambition rates on T.E. remain minimal, even in the presence of significant Carbon Trend levels. This suggests that while Carbon Ambition plays a role in influencing T.E., the overall cost of stringent Carbon Intensity Reduction targets or trends may be limited.

Figure 7: Multi-objective Efficient Frontier: Impact of Carbon Constraints



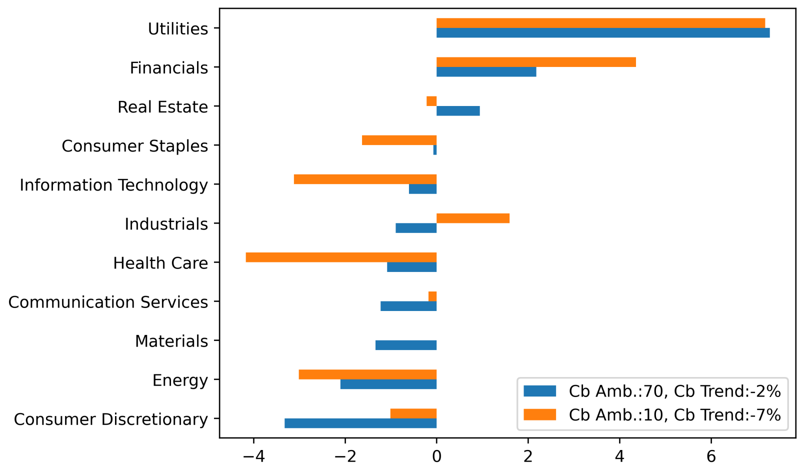
(a) Cb. Intensity vs. Ambition vs. Trend (b) T.E. Differences: CI Reduction 75%-0%

Illustrative Example Let us compare the active sectoral exposures of two portfolios with distinct decarbonization profiles. The first portfolio emphasizes an enhanced carbon trend, achieving a 10-year slope reduction of -7%, a moderate 2030 ambition target of -10%, and a current (spot) reduction rate of 50%. In contrast, the second portfolio reflects a modest historical reduction of -2% over the past decade but adopts an aggressive 2030 ambition of -70%. The first portfolio places greater emphasis on realized carbon trends while exhibiting limited future ambition, whereas the second prioritizes long-term ambition over observed historical progress.

The optimized portfolio sectoral composition can be explained by the data presented in Figure 8. The Figure shows the similarity and differences in sectoral bets of the two different profiles. The portfolio's overweight in sectors like Financials and Utilities is driven by the fact that the Financials sector has lower carbon emissions, and the Utilities sector has the lowest carbon trend. Indeed, Utilities have started to decarbonize earlier as the different requirement from IEA imposed a much more ambitious reduction for this sector (c.f. Sectoral Decarbonization Approach). Despite initial expectations, Information Technology is not overweighted because it has a high carbon trend, even though it exhibits high carbon ambition and low carbon emissions. However, if constraints are pushed further, particularly reduction rate and ambition constraints, Information Technology would have more weight. The Energy sector, on the other hand, has experienced a significant underweighting due to the stringent reduction rate and carbon trend constraint. The carbon trend profile overweights Industrials and neutral on Real Estate, Comm. Services, Materials, and by contrast, the carbon ambition profile underweights these sectors.

Figure 8: Illustrative portfolio: relative weight sector composition

The x-axis represents the relative weight of sector betweent the portfolio and the benchmark



In Table 7, we present the reduction in Tracking Error (T.E), ex-post in percentage, of the green portfolios compared to the baseline tracker, along with associated turnover two way. The formation and rebalancing of portfolios are conducted in the same manner as described in Section 3.1. Notably, the short-term ex-post tracking error profile of the climate-targeted portfolio remains quite similar to that of the green trackers, and only slightly higher than that of the baseline trackers, even when the target metrics are set higher.

Table 7: T.E.(ex-post) and Turnover of constrained portfolios as of 31/12/2023

	T.E. (ex-post, in bps)				Turnover(%)
	1M	2M	3M	6M	
Baseline Trkr(+24.09, 6, 34.37)	195.96	225.73	214.97	197.99	x
Green Ptfs (0,-5, 60)	311.47	297.20	293.28	294.70	54.82
Green Ptfs (0,-10, 60)	358.40	337.70	344.98	341.66	63.02
Green Ptfs (0,-15, 60)	399.81	386.60	402.15	408.00	74.91
Green Ptfs (-50,-5, 60)	318.10	300.92	293.86	293.66	55.24
Green Ptfs (-50,-10, 60)	362.67	340.35	345.16	340.85	63.38
Green Ptfs (-50,-15, 60)	399.81	386.60	402.15	408.00	74.91
Green Ptfs (-75,-5, 60)	358.95	335.15	326.58	312.99	57.76
Green Ptfs (-75,-5, 70)	379.84	346.55	359.61	354.07	66.99
Green Ptfs (-75,-5, 80)	415.28	393.30	397.41	425.72	77.04
Green Ptfs (-75,-10, 60)	392.28	365.80	372.49	359.34	65.95
Green Ptfs (-75,-10, 70)	429.12	390.87	395.45	401.42	73.60
Green Ptfs (-75,-10, 75)	451.35	428.51	426.37	457.82	81.10

Note: the numbers in the parentheses read as: (Carbon spot intensity Reduction (%), Carbon Trend (10Y trend slope), Carbon Ambition proxied by the company's carbon reduction commitment by 2030), linearized as in Le Guenedal *et al.* (2022).

3.3 Price Evolution of the Climate Portfolios

In this section, we present the risk metrics of the portfolios discussed in Sections 3.1 and 3.2 during the years 2021 to 2024, namely annualized volatility, beta and maximum draw-down (max DD). Portfolios are formed and rebalanced at the end of each year and maintained throughout the calendar year. We reiterate that the portfolios are constructed under the following three constraints: Carbon intensity spot Reduction, Carbon Trend (10 years) and Carbon Ambition by 2030. The Green Trackers demonstrate risk characteristics that closely aligns with the benchmark and the baseline tracker, while exhibiting more environmentally-friendly characteristics. Overall, the out-of-sample T.E increases from 285.17 bps to a range of 500 bps - 600 bps of green trackers with the allowed T.E ex-ante budget up to 450 bps.

Conversely, the more rigorously controlled portfolios, e.g., the most aggressive portfolios from a climate-target point of view (75,-10,75) exhibit a light increase in terms of volatility and drawdown while being tilted toward the greener but riskier sectors, such as Financials and Information Technology. These portfolios overall outperform the benchmark in the observed period, despite quite a strict set of constraints applied in the construction (beta one, sector alignment). We'd like to remind that the selected porfolio is not the most performing portfolio in the period of backtest.

Table 8: Green Trackers Risk Metrics: 2021-2024

Tracker	**T.E(bps)**	**Ann. Vol(%)**	**Beta**	**Max DD(%)**
Baseline	285.17	14.68	1.06	-16.99
Green(300)	498.32	14.09	0.97	-18.84
Green(325)	511.76	14.11	0.97	-19.19
Green(350)	526.60	14.13	0.97	-19.45
Green(375)	545.89	14.16	0.96	-19.58
Green(400)	565.38	14.20	0.96	-19.77
Green(425)	583.63	14.25	0.96	-19.98
Green(450)	600.00	14.28	0.96	-20.19
Green(475)	613.49	14.34	0.96	-20.45
Green(500)	628.24	14.40	0.96	-20.65

Note: The number in parentheses represents the T.E ex-ante against the benchmark

The first set of results in Table 8 present the performance of Green Trackers across various levels of green exposure. As expected, Tracking Error (T.E.) increases monotonically with a greater green target, reflecting the deviation from the benchmark. The baseline (non-green) tracker portfolio exhibits the lowest T.E. at 285.17 basis points (bps), whereas Green (300) and Green (500) reach approximately 500 to 630 bps, underscoring the increased difficulty in closely tracking the benchmark as carbon-adjusted constraints become more stringent. Annualized volatility and beta remains relatively stable across the Green Trackers, fluctuating within a narrow range of 14%–14.40% and around 0.96 resp., indicating that introducing sustainability constraints does not materially alter portfolio risk in terms of volatility. However, a slight upward trend in volatility suggests a modest increase in risk as the portfolio incorporates higher sustainability constraints.

Regarding downside risk, maximum drawdown also exhibits a monotonic trend, with an increase of approximately 2% compared to the baseline. This result highlights the trade off between climate-aligned investing and capital preservation.

Table 9: Climate Targeted Portfolios Performance: 2021-2024

	T.E (bps)	**Ann. Vol** (%)	**Beta**	**Max DD** (%)	**Avg. Excess Return** (%, ann.) 2021	2022	2023	2024
Benchmark	x	13.57	1	-16.41	x	x	x	x
Green Ptf(0,-5,60)	201.92	14.50	1.05	-17.47	0.28	-0.79	2.52	-3.48
Green Ptf(0,-10,60)	244.16	14.63	1.05	-17.92	0.81	-0.95	2.03	-2.91
Green Ptf(0,-15,60)	310.73	14.80	1.05	-18.23	1.02	-1.13	2.06	-2.14
Green Ptf(50,-5,60)	201.55	14.51	1.05	-17.47	0.32	-0.81	2.52	-3.27
Green Ptf(50,-10,60)	243.88	14.63	1.05	-17.95	0.81	-0.98	2.04	-2.75
Green Ptf(50,-15,60)	310.76	14.80	1.05	-18.24	1.02	-1.13	2.06	-2.14
Green Ptf(75,-5,60)	213.36	14.61	1.05	-17.79	0.67	-1.46	1.82	-2.11
Green Ptf(75,-5,70)	245.86	14.68	1.05	-17.82	2.02	-0.99	3.30	-1.95
Green Ptf(75,-5,80)	314.54	14.83	1.05	-18.01	4.99	-1.40	4.92	-2.26
Green Ptf(75,-10,60)	255.45	14.74	1.06	-18.43	1.33	-1.44	1.25	-1.71
Green Ptf(75,-10,70)	297.60	14.79	1.05	-18.19	2.81	-1.08	3.42	-1.81
Green Ptf(75,-10,75)	343.47	14.88	1.04	-18.47	3.74	-1.18	3.83	-1.30

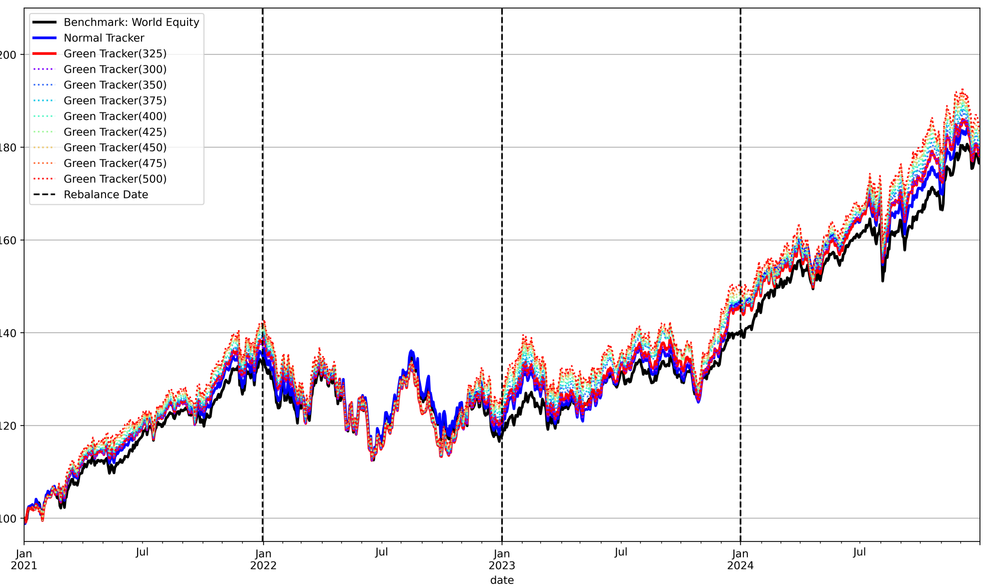
Note: the numbers in the parentheses read as: (Carbon intensity spot Reduction (%), Carbon Trend (10Y trend slope), Carbon Ambition proxied by the company's carbon reduction commitment by 2030).

Table 9 extends the analysis to Climate-Targeted Portfolios, incorporating explicit carbon intensity reductions, long-term carbon trend constraints, and engagement-based carbon ambition levels. The performance evaluation considers risk metrics and excess return decomposition across individual years. Similar to Green Trackers, the Climate-Targeted Portfolios exhibit modest variations in annualized volatility, with most configurations remaining between 14.03% and 14.27%. While the volatility differences appear minor, beta values show notable reductions, particularly for portfolios integrating stronger carbon constraints (e.g., Green Ptf(75,-15,80) with β = 0.96). The underlying anecdotal evidence is that deep decarbonization portfolios may benefit from lower systemic exposure, possibly due to shifts in industry allocations favoring more defensive, less market-sensitive stocks.

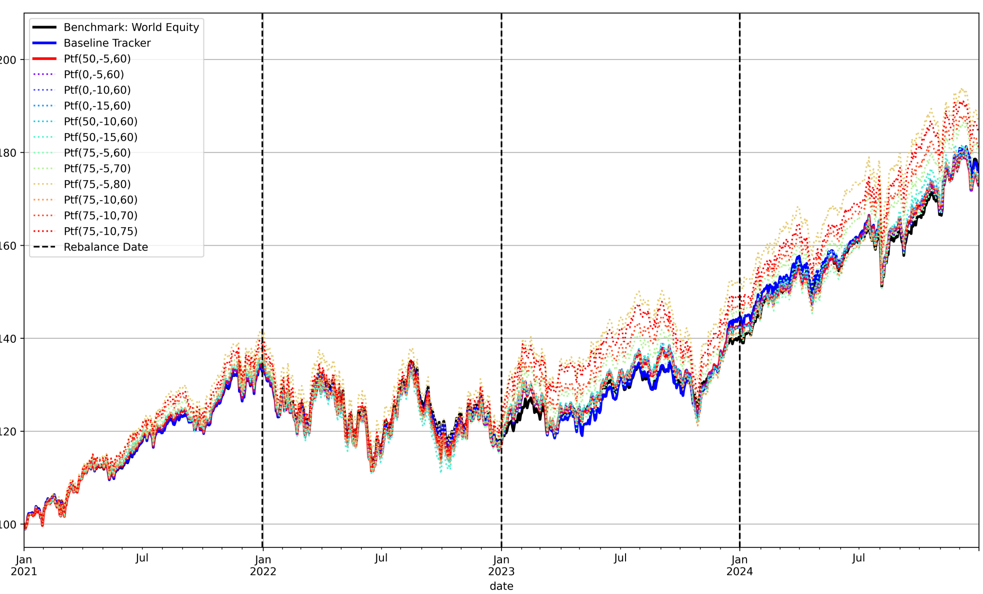
Importantly, maximum drawdown shows significant heterogeneity across portfolios. While moderate carbon constraints (e.g., Green Ptf(0,-15,60) at -15.72%) exhibit improved downside risk relative to the benchmark (-16.66%), stronger carbon ambition portfolios do not consistently offer better drawdown characteristics. For example, Green Ptf(75,-15,80) experiences a maximum drawdown of -17.45%, reflecting potential vulnerabilities to market corrections. This non-linear pattern suggests that while climate-aware investing may enhance resilience, excessively stringent constraints may introduce unintended downside exposure.

A key consideration is the excess return profile across different carbon-intensity constraints. Overall, the green-tilted portfolios underperformed the benchmark in bearish market conditions (2022), whereas they overperformed in bullish markets (2021, 2023, 2024). This provides illustrations that in the past market environments, aligning portfolios with sustainable targets offered competitive performance benefits, particularly during bullish market phases. Indeed, portfolios with moderate carbon constraints (e.g., Green Ptf(0,-15,60)) outperform across 2021-2024 (except in 2022), delivering an annualized excess return of 1.90%, -1.37%, 2.90%, and 2.69%, respectively. More aggressive sustainability constraints exhibit

Figure 9: Climate portfolios performance



(a) Green Trackers



(b) Climate Targeted Portfolios

mixed performance, with some portfolios experiencing higher drawdowns and return volatility. Indeed less diversified portfolios will have more diverse responses to different market conditions. For instance, Green Ptf(75,-15,80), which integrates both high spot-intensity reductions and engagement-based ambitions, delivered strong returns in 2023-2024 (6.75% and 8.18%) but suffered in 2022 (-3.20%). This suggests that while deep decarbonization strategies offer potential upside in specific market conditions and that the less diversified portfolios will have more diverge responses to different market conditions. Thus, they may be subject to greater cyclical performance swings.

Previous research (Burnichon *et al.*, 2024) illustrate that, the excess return patterns are sensitive to market conditions. The underperformance in 2022 for most green portfolios reflects a broader market rotation toward high-carbon sectors amid macroeconomic headwinds (e.g., energy price shocks). Indeed, the energy sector is largely underrepresented for high levels of Green Signal, as shown previously on 14 which penalized the performance of green portfolios. Conversely, strong returns in 2023 and 2024 for high-constraints portfolios suggest that markets reward firms with strong climate credentials when economic conditions stabilize, namely through a an overweight on Financials and IT.[21]

An essential trade-off in sustainable investing is balancing tracking error against increase in sustainability of the portfolio. Climate portfolios with higher T.E. (e.g., Green Ptf(75,-15,80) at 415.16 bps) tend to exhibit higher return dispersion over time, implying that while sustainability-focused strategies offer potential upside, they also introduce significant benchmark deviations. In contrast, moderate-constraint portfolios (e.g., Green Ptf(0,-10,60) with 199.78 bps T.E.) maintain a more stable excess return profile across different market cycles, suggesting a more balanced risk-return tradeoff.

The results highlight three key insights for investors considering climate-conscious portfolio construction. Portfolios with moderate decarbonization objectives (e.g., Green Ptf(0,-15,60)) exhibit competitive performance with reduced downside risk, making them an attractive alternative to conventional benchmarks. While deep decarbonization strategies (e.g., Green Ptf(75,-15,80)) can deviate substantially either positively or negatively depending on the market conditions. They introduce higher drawdown risk and excess return volatility, suggesting the need for careful risk budgeting. Higher carbon reduction constraints lead to higher tracking error, raising questions about investor risk tolerance. Portfolios with moderate green exposure balance sustainability objectives without excessive deviations from traditional benchmarks.

Tables 10 and11 together with Figures 10a and 10b present the performance attribution[22] of the green portfolio (75,-15,75) by GICS sectors, for the most recent year (2024) and the year that contribute the most to the over-performance of the green portfolios (2023). In 2023, the strongest sources of active return were the Financials, Info. Tech., and Health Care sectors, contributing approximately +2.54%, +2.59%, and +1.61%, respectively. These positive contributions were primarily driven by selection effects (+2.51% in total), i.e the out-performance of stocks chosen under the green investment constraints. Conversely, the green-tilted stock selection within Comm. Serv., Industrial and Cons. Disc. detracted from performance. Furthermore, the model successfully underweights Health Care to enhance overall returns.

In 2024, the Financials and Health Care sectors remain the primary drivers of performance, contributing 0.8% and 0.37%, respectively. They are accompanied by the positive impacts from Consumer Discretionary and Utilities, which contributed 1.67% and 0.64%,

[21] Sectoral and geographical biases are exposed in Bhaugeerutty (forthcoming).

[22] following Brinson-Hood-Beebower model in Brinson *et al.* (1986)

Table 10: Performance Contribution in 2023 by GICS Sectors (%)

Green Portfolio (75,-15,80)

	Effects				
	Alloc.	**Select.**	**Interaction**	**Sum**	**Act. Ret.**
Comm. Serv.	-0.42	-0.86	0.49	-0.79	-1.20
Cons. Discr.	0.29	-1.54	-0.45	-1.70	-1.30
Cons. Staples	0.46	0.55	-0.20	0.80	0.40
Energy	0.43	-0.18	0.09	0.34	-0.07
Financials	-0.20	1.91	0.42	2.14	2.54
Health Care	0.50	1.90	-0.39	2.02	1.62
Industrials	0.05	-1.28	-0.30	-1.53	-1.20
Info. Tech.	0.66	1.33	0.19	2.18	2.59
Materials	0.15	0.37	-0.27	0.25	-0.15
Real Estate	-0.04	0.37	0.07	0.40	0.47
Utilities	-0.55	-0.06	-0.06	-0.67	-0.27
Total	1.33	2.51	-0.41	3.43	3.43

Table 11: Performance Contribution in 2024 by GICS Sectors (%)

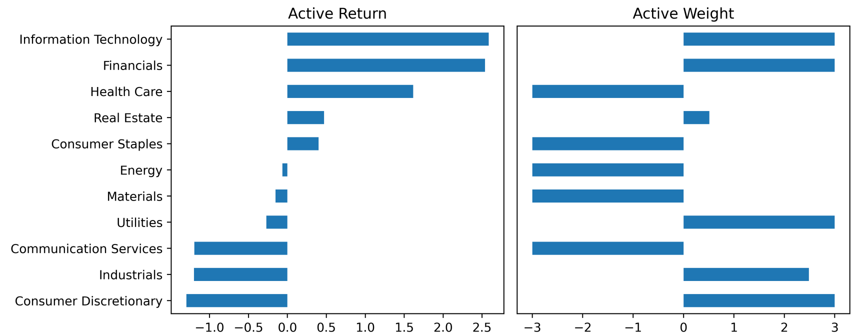
Green Portfolio (75,-15,80)

	Effects				
	Alloc.	**Select.**	**Interaction**	**Sum**	**Act. Ret.**
Comm. Serv.	-0.42	-1.99	0.98	-1.44	-2.03
Cons. Discr.	0.10	0.78	0.21	1.08	1.67
Cons. Staples	0.31	-2.66	1.17	-1.19	-1.77
Energy	0.36	-1.22	0.79	-0.06	-0.65
Financials	0.31	-0.07	-0.02	0.22	0.80
Health Care	-0.09	0.32	0.02	0.25	0.37
Industrials	-0.05	-0.84	-0.09	-0.98	-0.76
Info. Tech.	-0.15	0.48	-0.03	0.30	-0.05
Materials	0.66	-0.67	0.50	0.48	-0.10
Real Estate	-0.35	-0.20	-0.24	-0.79	-0.20
Utilities	-0.13	0.09	0.10	0.05	0.64
Total	0.55	-5.98	3.39	-2.08	-2.08

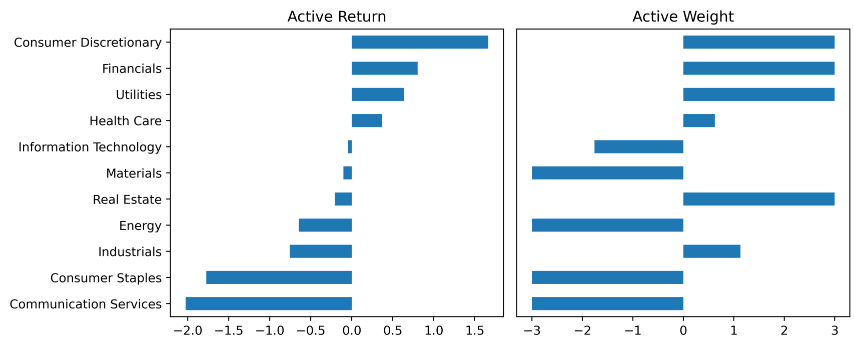
respectively. On the other hand, the Communication Services sector continues to lag, with a negative return of -2.0%, while Consumer Staples follows closely with a -1.77% return. The performance of the portfolio aligns with its strategic overweighting of the top-performing sectors, while the underweighting is not effective.

We conduct a further analysis of the excess return of the Green portfolio (75,-10,75) using traditional Fama-French factor models, both with and without Carhart's momentum

Figure 10: Active Weights and Active Return (in %)



(a) 2023



(b) 2024

factor. The results, as shown in Table 12, [23] indicate that none of the traditional factors accurately explain the behavior of the Green portfolio. While the α values are weak, they remain statistically significant across all model specifications.

[23] The values in parentheses in Table 12 represent t-statistics, and factors marked with an asterisk are statistically significant.

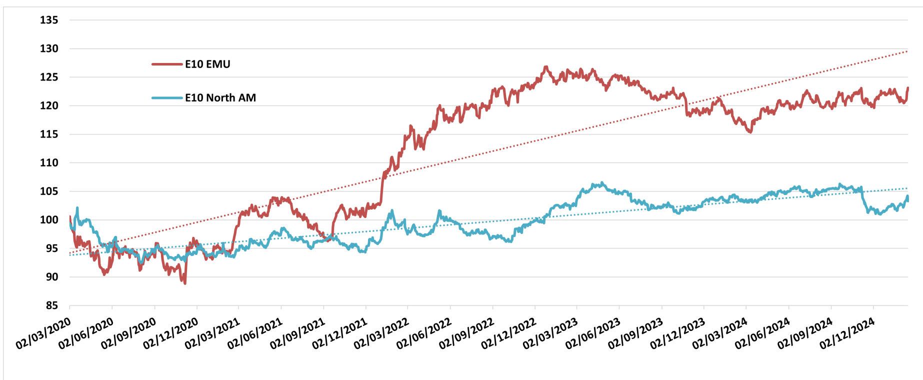
Table 12: Illustrative Green Portfolio Return Decomposition on Fama-French Factor Models

α	**Mkt-RF**	**SMB**	**HML**	**RMW**	**CMA**	**WML**	**adj R^2**
0.01*	0.91*	-0.05	0.03	0.12	-0.25	-0.17	83.70%
(2.60)	(12.90)	(-0.22)	(0.10)	(0.44)	(-0.67)		
0.01*	0.93*	0.04	0.13	0.22	-0.34		83.30%
(2.54)	(13.11)	(0.21)	(0.52)	(0.87)	(-1.11)		
0.01*	0.93*	-0.64	-0.14			-0.20	84.10%
(2.88)	(13.40)	(-0.33)	(-1.24)			(-1.35)	
0.01*	0.97*	0.02	-0.11				83.20%
(2.67)	(12.82)	(0.09)	(-1.10)				

The illustrative portfolio constraint setting is CI: 75%, Trend: -0.10, Ambition: 75%.

Performance of Sector Neutral Long-short (E10) Portfolios

Following the methodology first introduced in Bennani *et al.* (2018) and later expanded by Drei *et al.* (2019) and Lepetit *et al.* (2021), which entails continuously monitoring the performance of ESG factors and sub-pillars in the equity markets, we gain insights into the impact of reduced sectoral flexibility on optimization constraints. ESG scores are calculated as z-scores to ensure sufficient sector neutrality. Building on this centering process, the long-short portfolio is constructed by selecting the top 20% and bottom 20% of issuers within each sector, all while adhering to benchmark constraints. The following chart displays the performance of the long-short portfolio using the E10 score, which reflects carbon emissions and intensities.



Notably, the superior performance of best-in-class over worst-in-class issuers—evidenced by the overall positive trend in the long-short portfolio across both regions—suggests that the sector allocation effect alone does not account for the market reward associated with a green portfolio.

Discussion The performance of green portfolios reported in Table 9 varies significantly in different years, which can be linked to geopolitical, macroeconomic, and scientific developments. In 2021, favorable returns can be attributed to post-pandemic economic recovery and increased governmental support for green investments, or adapted fiscal policies as suggested in Zhang (2023) for example, for low-carbon intensive company. Studies have shown that green bonds and environmentally focused investments had gained traction during this period, reflecting growing investor preference for sustainable assets. The downturn in 2022 aligns with the global energy crisis following geopolitical tensions. Research indicates that energy price shocks led to a market shift toward high-carbon sectors such as fossil fuels. Furthermore, rising interest rates in response to inflation concerns negatively affected growth-oriented and green investments.

The mixed performance in 2023 and 2024 reflects the interplay of policy shifts and technological advancements. The period being marked by monetary policy tightening this can lead to a relative outperformance of green portfolios. For example, Patozi (2023) found that companies with strong environmental performance tend to face smaller declines in stock prices than those with weaker environmental records when monetary policy becomes more restrictive. While new climate regulations and increased corporate commitments to net-zero goals provided tailwinds for green assets, market, scenario uncertainties, as well as sectoral rotations influenced year-to-year fluctuations. These findings highlight the sensitivity of green investments to macroeconomic and geopolitical events, reinforcing the importance of strategic risk management when constructing climate-conscious portfolios.

Overall, the findings suggest that climate-aware investing does not inherently compromise financial performance but requires strategic calibration to optimize risk-adjusted returns. Investors seeking sustainability without excessive risk should favor portfolios with moderate decarbonization objectives, whereas those prioritizing impact over benchmark fidelity may benefit from higher-intensity green portfolios with greater return dispersion potential.

The Participation, Ambition, and Credibility (PAC) alignment metrics used in this analysis stand in contrast to the risk metrics most commonly employed by asset managers, such as Value at Risk (VaR), market Carbon beta (the Brown minus Green Risk Factor), and conditioned Probability of Default (PD). While the latter metrics primarily concentrate on downside financial risk, the PAC metrics evaluate the degree to which an investment portfolio aligns with strategic objectives pertaining to investor participation, growth ambition, and market credibility. Our methodology is nonetheless compatible with a diversity of climate metrics, such as the share of green revenues.

4 Conclusion

Institutional investors and regulators in Europe and Asia increasingly expect climate-signals. In this paper, we introduce alternative optimization programs and the objective function, to assess the impact of introducing carbon or climate constraints and objectives in the equity portfolio construction process. We illustrate with some case studies that portfolios with less 'spot decarbonization' constraints but higher trend and ambition constraints can be built and could have historically achieved similar performance. Our analysis reveals that while the initial removal of sector alignment constraints causes the rapid reduction of positions in polluting sectors, maintaining these constraints still ensures high green signal exposure with broad sector representation. Secondly, while the tracker is incrementally steered towards the "green" direction using a composite signal, green trackers demonstrate substantial improvements in Carbon Intensity Reduction, Carbon Trend, and higher Carbon Ambition compared to the baseline tracker.

Our study highlights the crucial role of advanced optimization methods in tackling the multidimensional complexity of portfolio management, particularly in the integration of climate-related constraints. While traditional portfolio optimization primarily balances risk and return, we demonstrate that leveraging multi-constrained optimization techniques allows for a more comprehensive approach, accommodating both financial and extra-financial objectives such as sustainability (Blitz *et al.*, 2024; M. Chen & Mussalli, 2020; Khan *et al.*, 2020). This methodology not only enhances computational efficiency but also enables the resolution of more complex problems compared to standard approaches seen in the optimization literature (ApS, 2024; Domahidi *et al.*, 2013). A key application of this innovation lies in the construction of climate-aligned benchmarks, such as Paris-Aligned Benchmarks (PAB), which require dynamic portfolio adjustments to comply with stringent decarbonization pathways (Desnos *et al.*, 2023; Le Guenedal & Roncalli, 2022). PAB indices, as defined by the European Commission, impose a significant reduction in carbon intensity at inception and an ongoing annual decarbonization trajectory, incorporating forward-looking climate scenarios (Bouchet & Le Guenedal, 2020; Roncalli *et al.*, 2020). Our findings illustrate how advanced optimization frameworks facilitate the integration of such constraints, making them valuable tools for investors seeking to align their portfolios with transition objectives.

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A Complementary Materials

A.1 Net-Zero Carbon Metrics Definitions

A.1.1 Carbon trend

We define the carbon trend by considering a linear constant trend model. The associated linear regression model is:

$$\boldsymbol{\mathcal{CE}}_i\left(t\right) = \beta_{i,0} + \beta_{i,1}t + u_i\left(t\right) \tag{1}$$

where $t \in \left[t_{\mathcal{F}irst}, t_{\mathcal{L}ast}\right]$. Using the least squares method, we can estimate the parameters $\beta_{i,0}$ and $\beta_{i,1}$. Then, we can build the carbon trajectory implied by the current trend by applying the projection:

$$\boldsymbol{\mathcal{CE}}_i^{\mathcal{T}rend}\left(t\right) \coloneqq \widehat{\boldsymbol{\mathcal{CE}}}_i\left(t\right) = \hat{\beta}_{i,0} + \hat{\beta}_{i,1}t \tag{2}$$

for $t > t_{\mathcal{L}ast}$. In this paper we use the slope computed with 10 year historical as a constraint.

A.1.2 Carbon Ambition

Carbon reduction targets are established by companies at the level of scope emissions, with varying time horizons. For example, a company may pledge to cut its scope 1 emissions by 50% over 20 years, while setting a goal of reducing its scope 3 emissions by 30% over 10 years. Although some targets extend up to 60 years, the majority focus on the next two decades. Targets can be set across different scopes and may have multiple announcement dates. This can lead to overlapping targets that are not always consistent. In such cases, it is necessary to determine whether the second target supersedes the first or if the two should be integrated.

We reiterate the definition in Le Guenedal *et al.* (2022). The carbon reduction target setting is defined from the following space:

$$\mathcal{T} = \left\{k \in \left[1, m\right] : \left(i, j, t_1^k, t_2^k, \boldsymbol{\mathcal{R}}_{i,j}\left(t_1^k, t_2^k\right)\right)\right\} \tag{3}$$

where k is the target index, m is the number of historical targets, i is the issuer, j is the scope, t_1^k is the beginning of the target period, t_2^k is the end of the target period, and $\boldsymbol{\mathcal{R}}_{i,j}\left(t_1^k, t_2^k\right)$ is the carbon reduction between t_1^k and t_2^k for the scope j announced by issuer i. The linear annual reduction rate for scope j and target k at time t is then given by:

$$\boldsymbol{\mathcal{R}}_{i,j}^k\left(t\right) = \mathbb{1}\left\{t \in \left[t_1^k, t_2^k\right]\right\} \cdot \frac{\boldsymbol{\mathcal{R}}_{i,j}\left(t_1^k, t_2^k\right)}{t_2^k - t_1^k} \tag{4}$$

Then, we aggregate the different targets to obtain the linear annual reduction rate for scope j:

$$\boldsymbol{\mathcal{R}}_{i,j}\left(t\right) = \sum_{k=1}^{m} \boldsymbol{\mathcal{R}}_{i,j}^k(t) \tag{5}$$

The budget approach consists in converting these reported targets into absolute emissions reduction as follows:

$$\boldsymbol{\mathcal{R}}_i\left(t\right) = \underbrace{\frac{1}{\sum_{j=1}^3 \boldsymbol{\mathcal{CE}}_{i,j}\left(t_0\right)}}_{\text{Total emissions}} \cdot \underbrace{\sum_{j=1}^{3} \boldsymbol{\mathcal{CE}}_{i,j}\left(t_0\right) \cdot \boldsymbol{\mathcal{R}}_{i,j}\left(t\right)}_{\text{Scope targeted reductions}} \tag{6}$$

Therefore, the carbon reduction $\boldsymbol{\mathcal{R}}_i(t)$ no longer depends on the scope and the target period. Once the reduction is established along the time horizon, the implied trajectory of the company emissions follows:

$$\boldsymbol{\mathcal{CE}}_i^{\mathcal{T}arget}(t) := \widehat{\boldsymbol{\mathcal{CE}}}_i(t) = \left(1 - \boldsymbol{\mathcal{R}}_i(t_{\mathcal{L}ast}, t)\right) \cdot \boldsymbol{\mathcal{CE}}_i(t_{\mathcal{L}ast}) \tag{7}$$

where:

$$\boldsymbol{\mathcal{R}}_i(t_{\mathcal{L}ast}, t) = \sum_{s=t_{\mathcal{L}ast}+1}^{t} \boldsymbol{\mathcal{R}}_i(s) \tag{8}$$

We can then compute the carbon budget according to the carbon targets declared by the issuer. In this paper, we use the truncated value of normalized reduction $\frac{\boldsymbol{\mathcal{CE}}_i^{\mathcal{T}arget}(2023)}{\boldsymbol{\mathcal{CE}}_i^{\mathcal{T}arget}(t_0)}$ where t_0 is the minimum base year of the company target.

A.2 Climate Metrics Descriptive Statistics

Table 13: Descriptive Statistics (as of 31/12/2023)

log_CIdirectFT	**mean**	**std**	**min**	**25%**	**median**	**75%**	**max**
All Samples	4.13	1.64	0.54	3.00	4.04	5.17	9.04
Communication Services	3.29	0.67	1.68	2.87	3.24	3.77	5.43
Consumer Discretionary	4.11	0.98	2.25	3.53	3.99	4.48	7.76
Consumer Staples	4.90	1.05	2.23	4.06	4.99	5.56	7.00
Energy	6.26	0.79	3.80	5.80	6.24	6.77	7.78
Financials	1.94	0.77	0.55	1.33	1.98	2.40	6.05
Health Care	3.67	0.77	0.83	3.41	3.75	4.04	5.73
Industrials	4.55	1.11	1.80	3.89	4.51	5.11	7.39
Information Technology	3.47	1.02	1.58	2.65	3.19	4.27	6.35
Materials	6.18	1.15	2.28	5.59	6.13	6.93	8.76
Real Estate	4.30	0.74	1.93	3.92	4.33	4.57	6.30
Utilities	6.51	1.52	2.23	5.73	6.54	7.67	9.04
Carbon Trend	**mean**	**std**	**min**	**25%**	**median**	**75%**	**max**
All Samples	0.03	0.14	-0.93	-0.04	0.01	0.08	1.65
Communication Services	0.06	0.17	-0.28	-0.03	0.01	0.12	0.95
Consumer Discretionary	0.04	0.17	-0.84	-0.03	0.02	0.07	1.27
Consumer Staples	0.02	0.09	-0.15	-0.03	0.01	0.05	0.57
Energy	0.05	0.14	-0.12	-0.02	0.01	0.08	0.69
Financials	-0.01	0.12	-0.68	-0.07	-0.02	0.04	0.55
Health Care	0.08	0.18	-0.30	-0.01	0.05	0.11	1.65
Industrials	0.02	0.11	-0.40	-0.04	0.01	0.05	0.71
Information Technology	0.08	0.14	-0.39	0.00	0.06	0.15	0.63
Materials	0.04	0.14	-0.27	-0.01	0.02	0.06	0.95
Real Estate	0.06	0.13	-0.22	-0.03	0.04	0.13	0.50
Utilities	-0.05	0.16	-0.93	-0.11	-0.04	0.02	0.23
Carbon Ambition	**mean**	**std**	**min**	**25%**	**median**	**75%**	**max**
All Samples	29.16	29.89	0.00	0.00	30.00	50.00	122.52
Communication Services	31.58	35.24	0.00	0.00	1.00	58.00	100.00
Consumer Discretionary	33.38	30.94	0.00	0.00	39.90	50.70	100.00
Consumer Staples	38.08	27.93	0.00	12.75	43.36	55.00	100.00
Energy	24.01	24.55	0.00	0.00	28.24	40.00	92.96
Financials	23.38	32.16	0.00	0.00	0.00	44.57	100.00
Health Care	31.97	31.66	0.00	0.00	32.50	50.00	100.00
Industrials	29.17	27.39	0.00	0.00	30.70	50.00	100.00
Information Technology	29.33	30.82	0.00	0.00	29.29	50.00	100.00
Materials	30.45	20.87	0.00	20.00	30.00	42.00	100.00
Real Estate	22.04	29.65	0.00	0.00	0.00	42.00	122.52
Utilities	28.92	31.48	0.00	0.00	20.95	55.44	100.00

Figure 11: Carbon Data by Sectors (a)

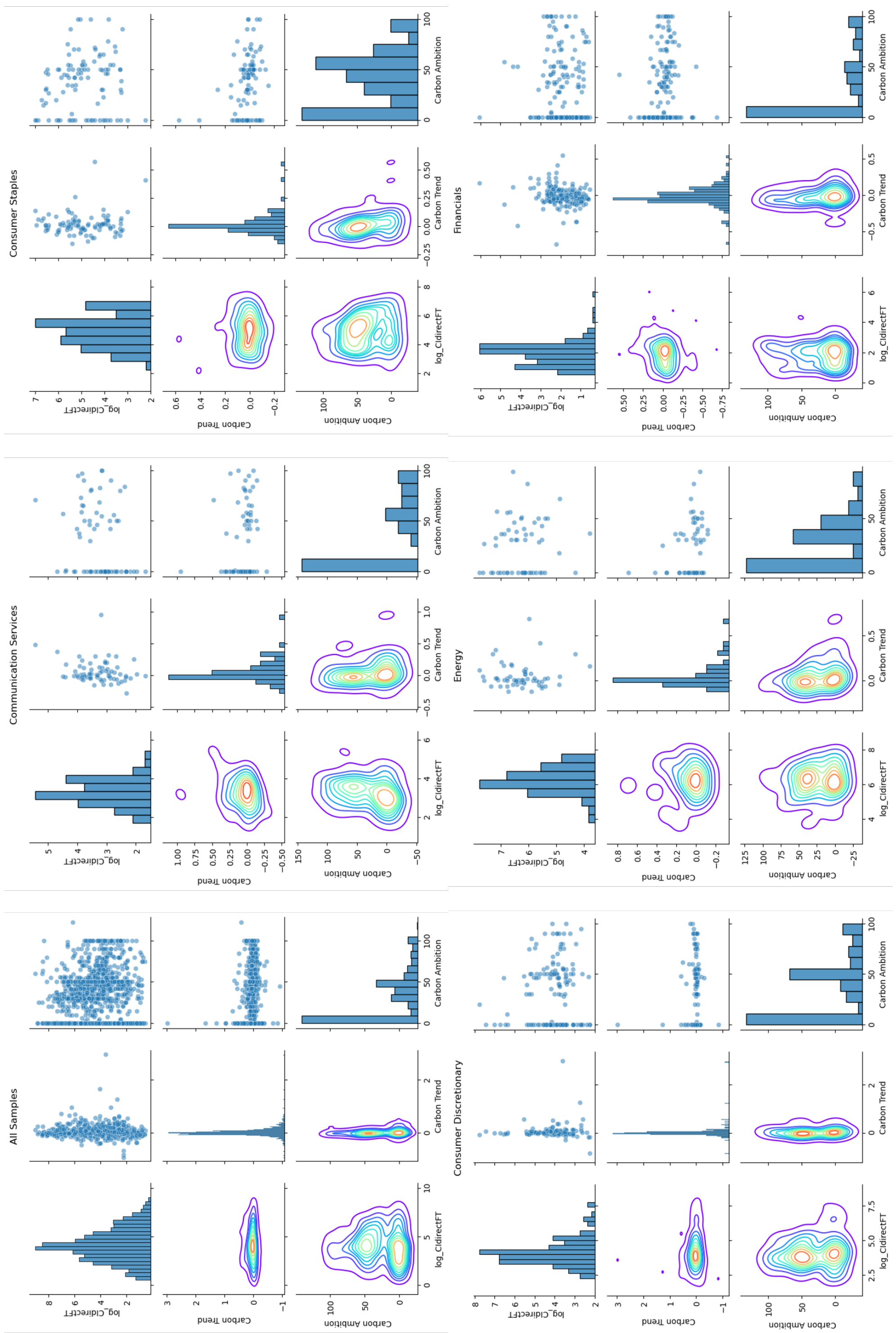
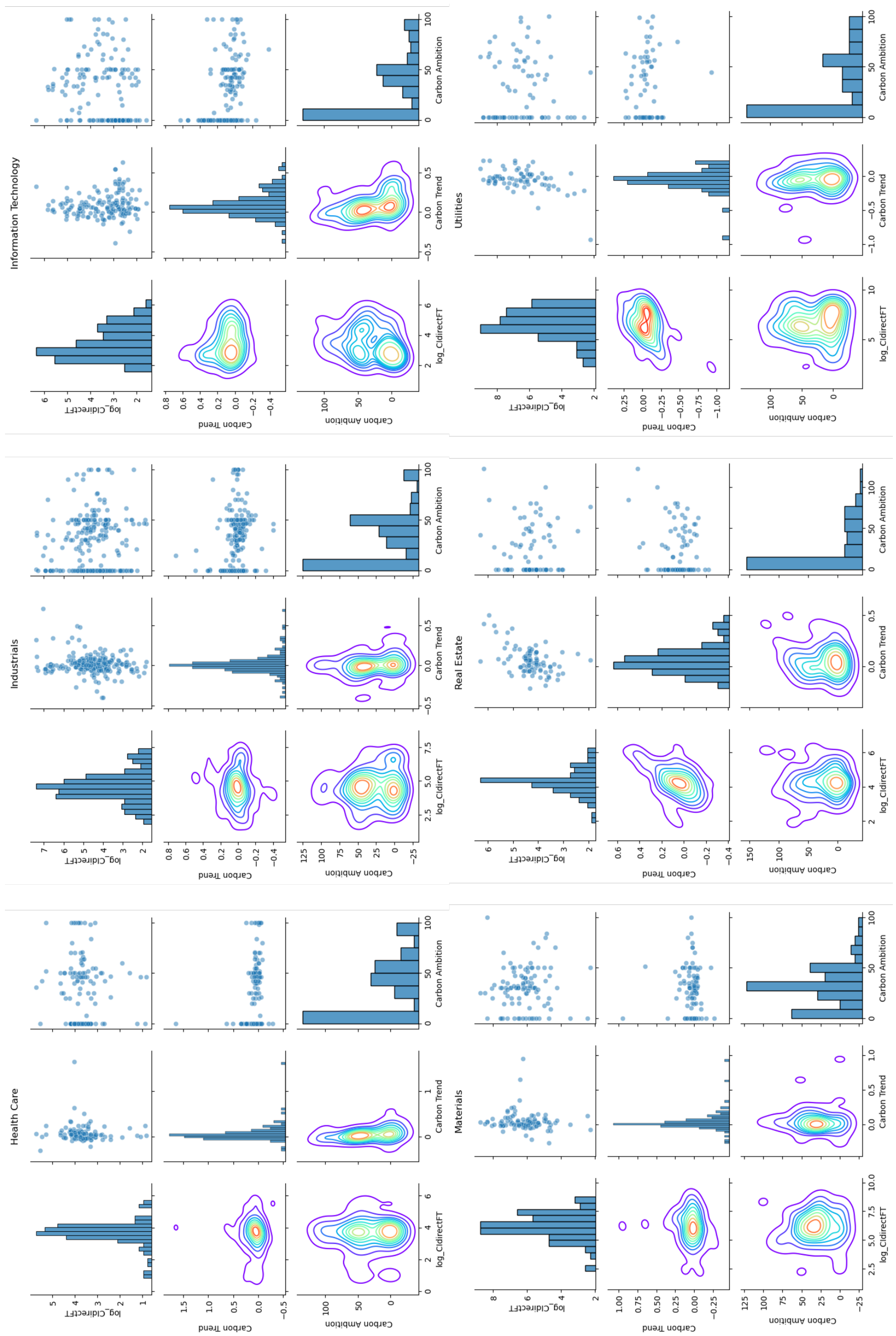


Figure 12: Carbon Data by Sectors (b)



A.3 Benchmarked Portfolio Management

Classical optimization problem The conventional portfolio optimization model is described by (Le Guenedal & Roncalli, 2022):

$$x^{\star}(\gamma) = \arg\min \frac{1}{2}(x-b)^{\top}\Sigma(x-b) - \gamma(x-b)^{\top}\mu \tag{9}$$

with constraints ensuring the sum of portfolio weights equals one and additional constraints, such as long-only positions or sector-specific weight limits. Climate considerations can be incorporated by adding a constraint to the optimization problem:

$$\Omega = \left\{x : \boldsymbol{\mathcal{C}}(x) = \sum_{i=1}^{n} x_i \boldsymbol{\mathcal{C}}_i \leq \boldsymbol{\mathcal{C}}^{+}\right\} \tag{10}$$

For instance, we may want to limit the portfolio's carbon emissions — $\boldsymbol{\mathcal{CE}}_j(x) \leq \boldsymbol{\mathcal{CE}}_j^{+}$ — or its carbon intensity — $\boldsymbol{\mathcal{CI}}_j(x) \leq \boldsymbol{\mathcal{CI}}_j^{+}$. We may also want to reduce the portfolio's carbon emissions or intensity with respect to a benchmark: $\boldsymbol{\mathcal{CE}}_j(x) \leq (1-\boldsymbol{\mathcal{R}})\boldsymbol{\mathcal{CE}}_j(b)$ or $\boldsymbol{\mathcal{CI}}_j(x) \leq (1-\boldsymbol{\mathcal{R}})\boldsymbol{\mathcal{CI}}_j(b)$ where $\boldsymbol{\mathcal{R}} > 0$ is the reduction rate. An alternative approach to Problem (10) is to formulate the following objective function (Le Guenedal & Roncalli, 2022):

$$\begin{aligned} x^{\star}(\gamma,\delta) &= \arg\min \frac{1}{2}(x-b)^{\top}\Sigma(x-b) - \gamma(x-b)^{\top}\mu + \gamma\boldsymbol{\mathcal{C}}(x) \\ &\text{s.t.} \quad \begin{cases} \mathbf{1}_n^{\top}x = 1 \\ x \in \Omega \end{cases} \end{aligned} \tag{11}$$

This condition sets upper limits on climate risk metrics like carbon emissions or intensity, directly impacting portfolio composition. An alternative approach involves a multi-dimensional trade-off between mean return, variance risk, and climate risk, which can be complex. The problem may be simplified by focusing on a dual trade-off between risk metrics and climate metrics, aligning with practical applications in active portfolio management. In summary, incorporating climate risks requires nuanced adjustments to traditional portfolio optimization frameworks, transforming how portfolios are constructed and managed to accommodate environmental objectives.

Portfolio decarbonization (Le Guenedal & Roncalli, 2022) A key topic in climate finance is portfolio decarbonization, which aims to construct a portfolio, x, that closely tracks a benchmark portfolio, b, while minimizing carbon pollution. We reiterate that this problem is formulated as follows[24] :

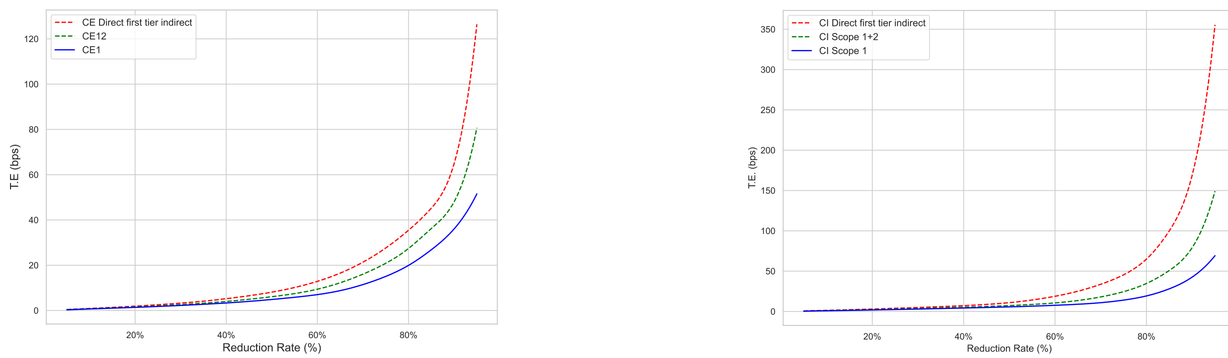
$$x^{\star}(\Delta) = \arg\min \frac{1}{2}(x-b)^{\top}\Sigma(x-b) \tag{12}$$

$$\text{s.t.} \quad \begin{cases} \mathbf{1}_n^{\top}x = 1 \\ x \geq \mathbf{0}_n \\ \sum_{i=1}^{n} x_i \boldsymbol{\mathcal{CI}}_i \leq (1-\Delta)\boldsymbol{\mathcal{CI}}(b) \end{cases} \tag{13}$$

[24]For simplicity, the subscript j is omitted in the subsequent notations.

where Δ is the reduction rate. This formulation minimizes the tracking error volatility between portfolio x and the benchmark b, subject to a long-only constraint and a reduced weighted average carbon intensity (WACI). The use of carbon intensity, rather than carbon emissions, may present issues for Net Zero carbon portfolios. The constraints lead to a portfolio x with fewer stocks than the benchmark b, dependent on the reduction rate Δ, the number of benchmark stocks n, and the covariance matrix, resulting in less diversification.[25] Furthermore, the Global Industry Classification Standard (GICS) sector constraints are implemented to prevent excessive portfolio concentration in specific sectors, promoting diversification.

Figure 13: Tracking error (T.E) versus the reduction rate (MSCI World Equity Index)



(a) TE vs. Reduction Rate of Carbon Emission (Absolute)

(b) TE vs. Reduction Rate Carbon Intensity

Note: plotted for different carbon intensity measures, including direct first tier indirect, CI Scope 1+2, and CI Scope 1, with GICS sector constraints of +/-5%.

The carbon intensity bound $\boldsymbol{\mathcal{CI}}^{(m,n)}$ is $\boldsymbol{\mathcal{CI}}^{(m,n)} = \boldsymbol{\mathcal{CI}}_{n-m+1:n}$, where $\boldsymbol{\mathcal{CI}}_{n-m+1:n}$ is the $(n-m+1)$-th order statistic. Eliminating the m worst-performing assets imposes $\boldsymbol{\mathcal{CI}}_i \geq \boldsymbol{\mathcal{CI}}^{(m,n)} \Rightarrow x_i = 0$. The resulting optimization problem is:

$$x^{\star}(m) \quad = \quad \arg\min \frac{1}{2}(x-b)^{\top}\Sigma(x-b) \tag{14}$$

$$\text{s.t.} \quad \begin{cases} \mathbf{1}_n^{\top} x = 1 \\ x \geq \mathbf{0}_n \\ \boldsymbol{\mathcal{CI}}_i \geq \boldsymbol{\mathcal{CI}}^{(m,n)} \Rightarrow x_i = 0 \end{cases} \tag{15}$$

This approach is termed the ‘order-statistic’ method, while the initial formulation is known as the ‘max-threshold’ method. As exposed in Le Guenedal and Roncalli (2022), a naive re-weighting solution is:

$$x_i = \frac{\mathbf{1}\left\{\boldsymbol{\mathcal{CI}}_i < \boldsymbol{\mathcal{CI}}^{(m,n)}\right\} \cdot b_i}{\sum_{k=1}^{n} \mathbf{1}\left\{\boldsymbol{\mathcal{CI}}_k < \boldsymbol{\mathcal{CI}}^{(m,n)}\right\} \cdot b_k} \tag{16}$$

[25] To control the number of excluded stocks, Andersson *et al.* (2016) proposed an alternative decarbonization method, eliminating the m worst-performing issuers in terms of carbon intensity. Let $\boldsymbol{\mathcal{CI}}_{i:n}$ be the order statistics of $(\boldsymbol{\mathcal{CI}}_1, \ldots, \boldsymbol{\mathcal{CI}}_n)$.

Figures 13a and 13b show the tracking error of six tilted portfolios. Figure 13a uses the absolute metrics in tons of $CO2_{eq}$ for the scope 1, scope 1+2 and direct, plus first tier indirect emission. This last metric refers to the upstream carbon emissions of the sector providing inputs to the industry.[26] This Figure suggests low costs of decarbonization, in terms of tracking error, when using this direct absolute carbon emission metrics. Using carbon intensity increase the T.E. cost (c.f. Figure 13a), because the underlying metric is less skewed (c.f. Le Guenedal and Roncalli, 2022). We confirm that the tracking error increase even further when considering indirect (or scope 3) emissions. In this paper, we introduce alternative optimization programs and the objective function, to assess the impact of introducing carbon or climate constraints and objective in the portfolio construction process.

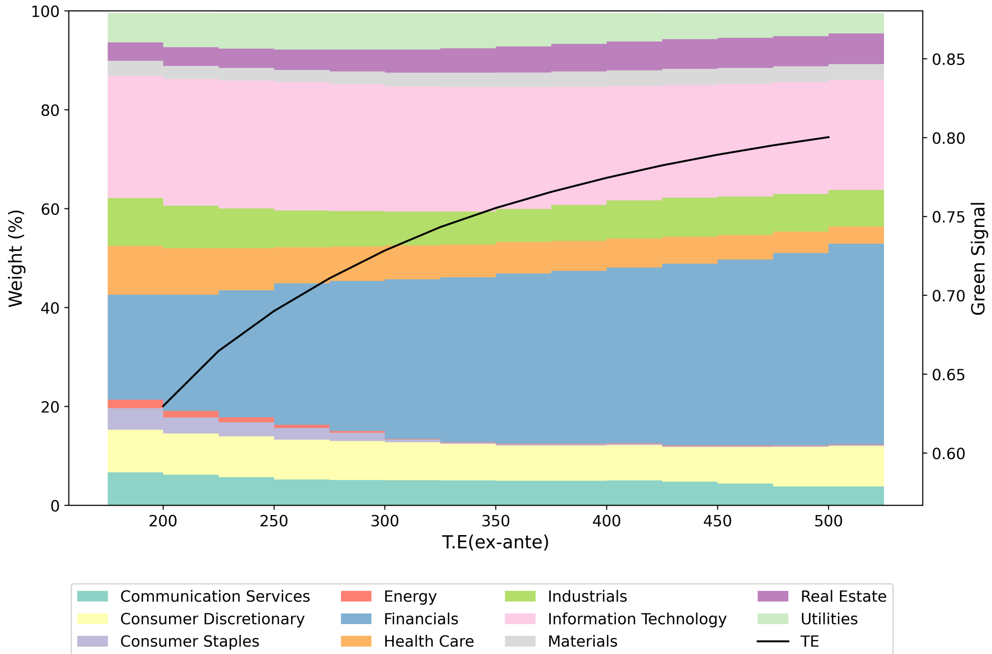
A.4 Statistics of Green Trackers

Table 14: Carbon Metrics of Green Trackers

Tracker	**Carbon Intensity**	**CI Reduction(%)**	**Carbon Trend**	**Carbon Ambition**	**Green Signal**	**T.O.**
Benchmark	176.12	x	5.75	36.11	0.52	x
Baseline Tracker	218.56	24.09	6.68	34.74	0.49	x
Green(200)	123.49	-29.89	0.06	51.45	0.63	42.85
Green(225)	110.23	-37.41	-1.28	55.80	0.66	53.35
Green(250)	102.92	-41.56	-2.26	59.43	0.68	59.96
Green(275)	94.23	-46.50	-3.21	62.02	0.70	64.47
Green(300)	82.69	-53.05	-4.16	64.12	0.72	67.69
Green(325)	73.62	-58.20	-4.97	65.70	0.73	70.03
Green(350)	67.86	-61.47	-5.59	66.75	0.74	72.41
Green(375)	63.91	-63.72	-6.12	67.22	0.75	75.08
Green(400)	58.48	-66.80	-6.68	67.47	0.76	78.17
Green(425)	47.79	-72.87	-7.22	67.68	0.77	80.51
Green(450)	39.47	-77.59	-7.75	68.00	0.77	83.02
Green(475)	36.09	-79.51	-8.09	68.55	0.78	85.40
Green(500)	35.47	-79.86	-8.21	68.79	0.78	86.16

[26]This metric is generally computed with input-output approach (Desnos *et al.*, 2023).

Figure 14: Efficient Frontier decomposed by sectors - with Sector constraints



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