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3D Investing: Implications for Net Zero

3D INVESTING: IMPLICATIONS FOR NET ZERO

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Traditional mean–variance portfolio optimization is based on the premise that investors care only about risk and return. Some investors, however, also have nonfinancial objectives, such as sustainability goals. Central to these goals, such as working toward net-zero emissions, is the question of how to incorporate such objectives into an investor's portfolio. We show how an extended mean–variance–sustainability optimization can incorporate sustainability goals into a portfolio, particularly aligning the portfolio with the net-zero transition set out in the Paris Agreement. Importantly, we compare various methods for integrating sustainability goals in investor portfolios and highlight the implications of such approaches on investor outcomes.

Introduction

Numerous approaches have challenged the standard risk-and-return portfolio framework. All of them focus on making investment decisions based on objectives that are not strictly risk or return based, such as impact investing, socially responsible investing (SRI), or environmental, social, and corporate governance (ESG) investing. Accordingly, investment practice has evolved to incorporate sustainability objectives into the investment problem, including metrics related to carbon footprint, ESG characteristics, and sustainability development goals (SDGs). In this chapter, we explore potential applications and implications of the 3D investing framework from Blitz, Chen, Howard, and Lohre (2024) in the context of net-zero transition alignment, as outlined in the Paris Agreement, adopted at the UN Climate Change Conference (COP21) in Paris on 12 December 2015.

The Paris Agreement is a landmark treaty in which 195 nations committed to limit global temperature rise this century to less than 2°C above preindustrial levels and pursue efforts to target an increase of less than 1.5°C. In 2018, the Intergovernmental Panel on Climate Change (IPCC) stated that carbon emissions need to reach net-zero neutrality by 2050 to limit global warming to 1.5°C (IPCC 2018). Achieving these ambitious climate and decarbonization

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goals requires investors to integrate net-zero transition objectives alongside traditional risk and return considerations, necessitating flexible portfolio construction frameworks.

Considering these ambitious climate and decarbonization goals, academics and practitioners have started developing new frameworks and toolkits to address the urgent need to decarbonize. At the center of this work is the concept of decarbonization pathways and trajectories toward net zero. These concepts can be seen as an evolution or extension of "low-carbon" portfolios, which aim to reduce exposure to assets with high carbon footprints at the moment of investment. Net-zero portfolios additionally aim to help transition the economy from "brown" to "green," which is inherently a more challenging forward-looking problem. Barahhou, Ben Slimane, Roncalli, and Oulid Azouz (2022) argue that constructing a net-zero portfolio is more complex than constructing a decarbonized portfolio because of the multi-objective nature of reducing portfolio carbon and financing the transition. At its core, the desire to construct net-zero-aligned portfolios is a multi-objective optimization problem.

Blitz et al. (2024) show how portfolio decarbonization can be achieved using both constraints and an objective function term and highlight how, for ambitious targets with low active risk budgets, the objective function term outperforms. The study's results show that for portfolios that seek to track the benchmark closely while outperforming it, ambitious sustainability goals are better implemented using a direct objective function term rather than a portfolio-level constraint. The objective function term allows for a rewarded time-varying trade-off of a stock's expected return and the stock's contribution toward the sustainability objective. It is this flexibility to decide at the portfolio construction's run time when it might be better to go for expected return vis-à-vis sustainability that gives the superior result of the objective function approach. In this chapter, we relate the concept of 3D investing to that of net-zero investing and the many-dimension problem of integrating net-zero objectives into a portfolio.

In recent years, the construction of net-zero portfolios has received considerable attention from both academics and practitioners. Bolton, Kacperczyk, and Samama (2022) propose a framework to align portfolios with a carbon budget that aims to keep global temperature rise below 1.5°C. This approach aims to maintain minimum tracking error to a market index while demonstrating the importance of time for reducing emissions. Le Guenedal and Roncalli (2022) survey how asset managers measures climate risk and constructs portfolios based on these climate risks. They highlight the importance of considering the impact of different carbon emission scopes and the challenges of integrating these objectives into the portfolio. Importantly, they highlight the nuance between portfolio decarbonization and portfolio alignment with Paris Aligned Benchmarks and net-zero carbon objectives. Jondeau, Mojon, and Pereira da Silva (2021) provide methodologies for constructing benchmark portfolios where the component companies' carbon footprint decreases over time.
In this chapter, we explore the applications and implications of a 3D investing

framework for the pressing challenge of constructing net-zero-aligned portfolios.

One of the key considerations with net-zero investing is balancing the long-term objective of reaching net zero by 2050 with the short- to medium-term objectives and incentives around balancing risk and return. Constructing net-zero portfolios is inherently a multi-objective problem, weighing decarbonization against financing the transition, risk, and return. Investors are balancing the urgency of decarbonizing the portfolio with the need to maintain the return and risk profile of the portfolios that they manage. Such a balance naturally requires a multi-faceted optimization approach that can incorporate numerous objectives alongside risk and return.

Specifically, in the context of net-zero investing, one mechanism could be to incorporate a forward-looking net-zero metric into the objective function and encourage the portfolio optimizer to take exposure to stocks based on expected returns, risk, and forward-looking net-zero expectations. If one considers incorporating Paris Aligned Benchmarks, these benchmarks effectively require a 50% carbon-intensity reduction relative to the benchmark based on current emissions, 7% year-on-year decarbonization, and adherence to several exclusions and exposure constraints. Meeting such objectives can naturally be achieved with both constraints and objective function terms. Blitz et al. (2024) show that for more ambitious carbon footprint reductions and lower tracking error targets, the objective function term helps reduce turnover and increase expected net outperformance.

Given the strict requirements of Paris Aligned Benchmarks, one could apply a portfolio construction paradigm that consists of portfolio-level constraints on current emissions, an objective function term on current emissions, and an objective function term on expected future emissions. Such an approach could allow for meeting the immediate-term requirements while also allowing the portfolio to take on greater exposure to decarbonization when it is "cheap" from an expected return or risk perspective. For example, if investors' expected return forecasts about highly emitting stocks are currently very negative, then they may be willing to take a larger underweight in such stocks if they also derive additional "net-zero utility" from such a position. Given that reducing current emissions is more valuable from a net-zero perspective than reducing future emissions, as shown by Daniel, Litterman, and Wagner (2019) and Fearnside, Lashof, and Moura-Costa (2000),[1] having a portfolio construction framework that can dynamically trade off return, risk, and net-zero objectives may lead to superior after-cost performance while meeting all stated objectives for integrating net-zero goals into the portfolio.

The question of how to integrate environmental objectives into an investment decision has been studied extensively. Repetto and Austin (2000) propose a

[1]This is the so-called time value of carbon. See the Wikipedia page on the topic: https://en.wikipedia.org/wiki/Time_value_of_carbon.

methodology to integrate environmental issues into the analysis of individual companies, using a scenario-based approach to evaluate the impact of emerging environmental issues on a company's operations. Barber, Morse, and Yasuda (2021) show how, in recent years, investors have begun to derive nonpecuniary utility when investing in dual-objective venture capital impact funds. They argue that investors are willing to sacrifice returns in pursuit of these alternative objectives.

Many approaches that strive to incorporate more general sustainability objectives into a portfolio have been proposed in the literature. These include excluding undesirable stocks from the investment universe (Diltz 1995; Kinder and Domini 1997; Naber 2001), constraining the portfolio's exposure to such objectives (Boudt, Cornelissen, and Croux 2013), and incorporating sustainable targets into the return/alpha component of the objective function (Steuer, Qi, and Hirschberger 2007; Bilbao-Terol, Arenas-Parra, and Cañal-Fernández 2012; Hirschberger, Steuer, Utz, Wimmer, and Qi 2013; Utz, Wimmer, Hirschberger, and Steuer 2014; Chen and Mussalli 2020).

The key tension of net-zero portfolio construction is the desired urgency of decarbonizing while meeting core risk and return objectives. All portfolio construction methods have different positives and negatives in considering these specific tensions. For example, divesting from high-carbon-emitting companies may significantly improve the immediate carbon profile of a portfolio, yet these companies may be best positioned to help develop and implement transitional technologies. Similarly, excluding a substantial portion of stocks may introduce significant added risk to a portfolio that is not within the risk budget. The investor's core focus is to balance these dimensions, and toolkits such as 3D investing can provide insights into how these dimensions interact in a portfolio.

In this chapter, we explore how a 3D investing framework could be applied to the challenge of constructing investment portfolios aligned with net-zero emission goals. Building on the work of Blitz et al. (2024), we show how integrating forward-looking climate metrics and emission pathway constraints into a multi-objective portfolio optimization could help investors navigate the complex trade-offs between decarbonization, performance, and risk. A 3D investing framework can allow for dynamic exposure to climate leaders and laggards based on return expectations and sustainability characteristics while adhering to decarbonization pathways. As investors grapple with the urgency of the net-zero transition, frameworks such as 3D investing will be useful tools for helping align portfolios on multiple dimensions.

The remainder of this chapter is organized as follows: In the next two sections, we outline the general multi-objective optimization framework and illustrate the use of 3D investing for climate objectives. Then, we explore the implications and applications for net-zero portfolios. Finally, we provide concluding remarks.

Multi-Objective Optimization Framework

We begin by introducing the portfolio optimization framework that we work with. First, we specify the common mean–variance optimization framework, where the investor trades off maximizing expected returns while jointly minimizing risk. We then expand this optimization paradigm to a multi-objective optimization framework.

Standard Mean–Variance Optimization

Equation 1 shows the standard mean–variance optimization formula:

$$\begin{aligned}&\max_{\mathbf{w}} \circ \lambda \mathbf{w}'\boldsymbol{\mu} - \frac{\gamma}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w},\\ &\text{s.t. } \mathbf{w}'\mathbf{e} = 1,\end{aligned} \tag{1}$$

where

$\mathbf{w}$ is an $N \times 1$ vector of asset weights

$\boldsymbol{\mu}$ is an $N \times 1$ vector of expected returns

$\boldsymbol{\Sigma}$ is the $N \times N$ variance–covariance matrix

$\mathbf{e}$ is an $N \times 1$ vector of ones

λ and γ are scalar coefficients

Portfolios generated under Equation 1 are mean–variance optimal in that they achieve the maximum expected return for a given level of risk. This framework can be extended to include additional dimensions, such as constraining the portfolio relative to some benchmark (Jorion 2003), incorporating transaction cost penalties (Taksar, Klass, and Assaf 1988; Ledoit and Wolf 2022), penalizing turnover (Hautsch and Voigt 2019), or enforcing positive asset weights (Jagannathan and Ma 2003). Ibbotson, Idzorek, Kaplan, and Xiong (2018) explore a popularity asset pricing model (PAPM) where they introduce additional "popularity" characteristics into the standard CAPM framework. Such an approach generalizes the standard mean–variance optimization problem to any number of alternative objectives. Steuer, Qi, and Hirschberger (2007) derive analytical solutions for an efficient portfolio surface with three criteria, using portfolio liquidity as an example. They extend the classical two-mutual-fund theorem to a three-mutual-fund theorem and show how the obtained three-dimensional efficient surface has paraboloidal/hyperboloidal structures.

A Multi-Objective Optimization Framework

It is straightforward to extend the mean–variance optimizer from Equation 1 to construct portfolios on an efficient frontier surface in three (or more) dimensions. In the case of additional sustainability considerations, Equation 1 can be extended to three dimensions as follows:

$$\max_{\mathbf{w}} \circ \lambda \mathbf{w}'\boldsymbol{\mu} + (1-\lambda)\mathbf{w}'\boldsymbol{\mu}_{SI} - \frac{\gamma}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w}, \quad \text{s.t. } \mathbf{w}'\mathbf{e} = 1, \mathbf{w} \in \Omega, \tag{2}$$

where $\boldsymbol{\mu}_{SI}$ is an $N \times 1$ vector of any (discrete or continuous) sustainability metric, λ becomes the relative preference between the return and sustainability objectives, and Ω is the set of feasible solutions, which includes any portfolio constraints. This formulation is general and can accommodate the incorporation of common sustainability characteristics. These include commercial ESG metrics from vendors, such as MSCI and Sustainalytics; carbon footprint; SDG scores; and climate transition scores. The only requirement here is that the sustainability metric is ordinal.[2]

Targeting a Climate Traffic Light

To illustrate how the 3D investing framework can easily integrate forward-looking climate measures, we use the simulation framework of Blitz et al. (2024) with the Robeco Climate Traffic Light (CTL) scores (Robeco 2022).[3] To summarize, we use an MSCI World Index developed markets universe alongside a simple expected returns model and variance–covariance matrix to conduct benchmark-relative portfolio optimization exercises.[4] Our sample consists of MSCI World constituents at the end of every month from December 1989 to December 2022.[5] We source stock returns and fundamental data from Refinitiv.

We use a portfolio optimization setting that mimics the construction of a real-life investment portfolio applying realistic portfolio constraints and settings. We construct portfolios with tracking errors of 0.5% because it represents the challenging multi-objective scenario of delivering high expected returns and sustainability goals with a limited risk budget. The portfolio exposure to regions (defined as North America, Europe, and Asia Pacific) and Global Industry Classification Standard (GICS) first-level sectors are restricted to ±0.5% of the benchmark market-capitalization-weighted value. Portfolios must be long only. The maximum trade size is limited to 25% of a stock's average daily volume over the past 65 trading days (ADV). The maximum stock weight relative to

[2]For practical considerations on the sustainability metric, $\boldsymbol{\mu}_{SI}$, see Chen and Mussalli (2020).

[3]We additionally use the data simulation approach of Blitz and Hoogteijling (2022) to produce a longer history of carbon footprint data and SDG data. Note that any potential forward information leakage is of little concern because we are comparing two portfolio construction approaches using the same data. We aim to illustrate the broad application of our methodology on a representative set of sustainability data.

[4]For full details on the portfolio implementation, see Blitz et al. (2024).

[5]Prior to 2001, we use constituents of the FTSE Developed Markets index as a proxy for MSCI World constituents.

the benchmark (i.e., active weight) is ±0.5%. The maximum active share of the portfolio is 40%. The portfolio must be fully invested. We assume that the funds under management grow with the realized market return, and we design the simulations such that the final fund size at the end of 2022 is EUR4 billion. We incorporate a turnover penalty into the objective function, which is the sum of the squared absolute trade sizes.

As we target specific tracking errors, we transform the weight vector of Equation 2 from absolute asset weights to benchmark-relative weights:[6]

$$\mathbf{w}_{new} = \mathbf{w}_p - \mathbf{w}_{bm}.$$

Our portfolio optimization problem for a single time step is then given by

$$\max_{\mathbf{w}} \circ \lambda_1 \mathbf{w}'_{new}\boldsymbol{\mu} + \lambda_2 \mathbf{w}'_{new}\boldsymbol{\mu}_{SI} - \frac{\gamma}{2}\mathbf{w}'_{new}\sum \mathbf{w}_{new} - \kappa \left\| \mathbf{w}_{new} - \mathbf{w}_{old} \right\|, \tag{3}$$

where $\mathbf{w}_{old}$ represents the portfolio weights immediately before the rebalance, κ is a scaling parameter for the turnover penalty (we set $\kappa = 1$), and we incorporate the previously described constraints. We use a base set of portfolio construction constraints and settings across our simulations, and then we permute the expected return coefficient (λ_1), the risk aversion coefficient (γ), and the sustainability coefficient (λ_2) in each different optimization. Lastly, we introduce an additional optional constraint on either carbon footprint or SDG scores (e.g., the portfolio carbon footprint must be less than or equal to the benchmark carbon footprint.)

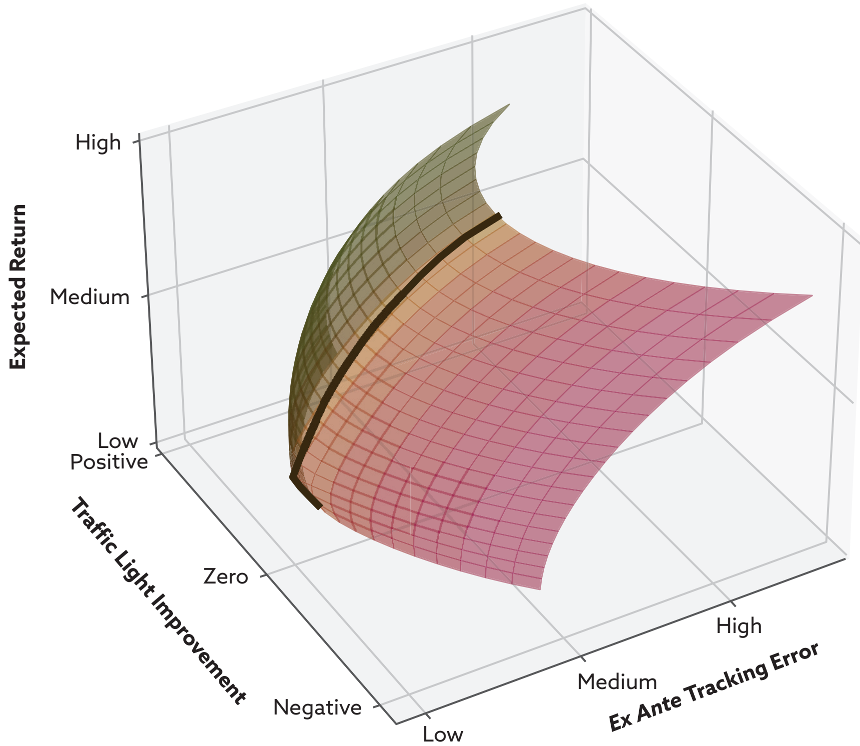
As inputs of expected returns μ, we use a simple equal-weighted multifactor score (denoted QMV) consisting of value, quality, and momentum signals. For value, we use an equal-weighted combination of book to price and 12-month forward earnings to price, ranked within GICS sectors. For quality, we use an equal-weighted combination of return on equity and debt to assets. For momentum, we use the previous 12-minus-1-month return. Each of the four underlying signals is first rank standardized between –1 and +1. The signals are then combined into a single multifactor score. We aim not to construct the best multifactor score but rather to construct a simplified score that represents common choices and implementations of multifactor investment strategies.

As for expected risk, we use a standard variance–covariance (VCV) matrix (Σ) that follows a latent factor model approach where we apply principal component analysis (PCA) with 20 components to the sample VCV matrix estimated using 60 months of daily return data. We use five-day overlapping returns to account for market asynchronicity (Burns, Engle, and Mezrich 1998).

Exhibit 1 shows the *ex ante* view of expected returns, *ex ante* tracking error, and CTL improvement over the benchmark as of December 2023. By mapping out a 3D surface of these elements, we can see how the objective of taking on more

[6]We use the same benchmark, the MSCI World, when constructing portfolios and evaluating financial and sustainability objectives.

Exhibit 1. Climate Traffic Light Efficient Surface

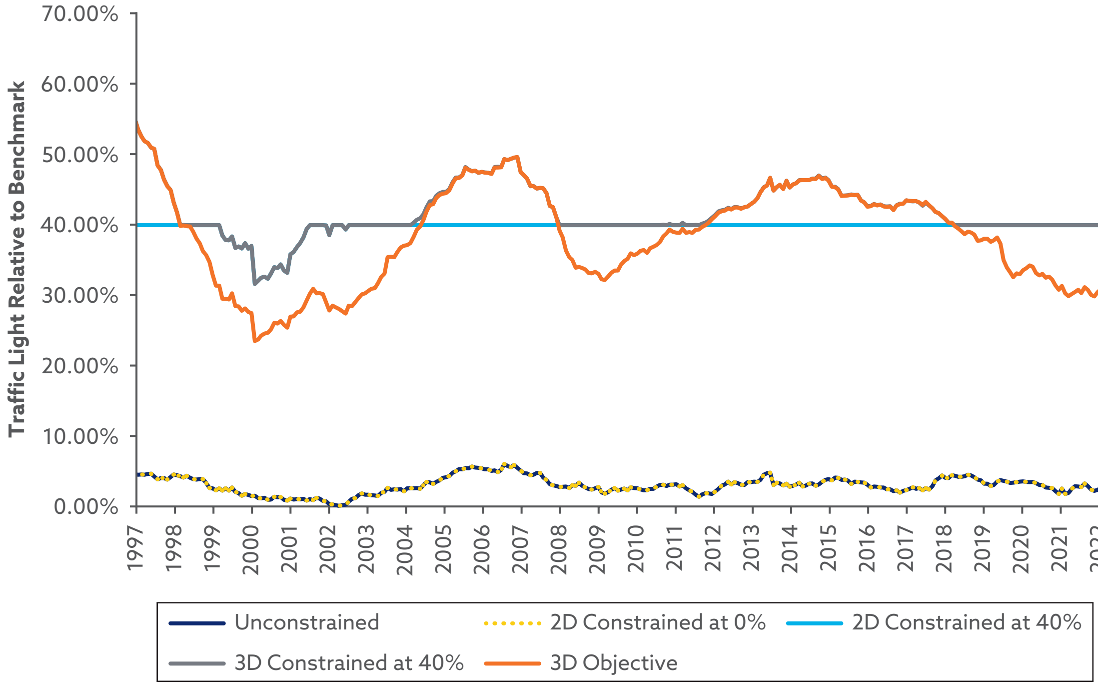


Note: This graph plots the *ex ante* expected return/tracking error/sustainability surface for Robeco's climate traffic light. The solid black line corresponds to the *ex ante* expected return/tracking error efficient frontier (i.e., the traditional case where only risk and return are considered). The surface is shaded based on the *y*-axis variable (climate traffic light relative to the benchmark), where green corresponds to a higher improvement and magenta corresponds to a lower improvement. This surface was calculated using data as of December 2023.

exposure to positive forward-looking climate stocks affects the risk and return characteristics of the optimal portfolios. In line with expectations, as the desire to integrate an alternative objective (which is not necessarily correlated with expected returns) into the portfolio increases, this integration requires either increasing tracking error or reducing expected returns.

Exhibit 2 compares the historical CTL profiles of portfolios constructed using different optimization approaches. It illustrates how the time-varying nature of a 3D investing approach can vary in comparison to a strict constraint. The dark blue line at the bottom represents an unconstrained portfolio that seeks to maximize expected excess returns without any consideration of CTL scores. This exposure is identical to the CTL improvement that is at least as good as the benchmark ("2D Constrained at 0%" yellow dotted line), suggesting that this constraint is not binding at any time. The "2D Constrained at 40%" bright blue line represents a portfolio that targets a minimum 40% CTL improvement relative to the benchmark at each rebalancing date, using a 2D optimization approach with a hard constraint on the minimum CTL score. The "3D Objective" orange line represents a CTL improvement using a 3D optimization approach. The "3D Constrained at 40%" gray line represents a portfolio that targets a minimum 40%

Exhibit 2. Climate Traffic Light Improvement to MSCI World under Various Optimization Scenarios



Note: This figure plots the percentage improvement of the portfolio's climate traffic light exposure over the MSCI World climate traffic light exposure using different 2D and 3D portfolio construction approaches. We report results for a portfolio with a tracking error target of 0.5%.

CTL improvement using a 3D optimization approach. This approach allows for a flexible trade-off between the competing objectives because the optimizer can choose to exceed the 40% minimum CTL improvement if doing so is expected to enhance returns or reduce risk. Further, in the 1999–2000 period, we can see what happens when a constraint cannot be satisfied. At this point, the "2D Constrained at 40%" bright blue line is unable to meet the 40% constraint and thus is forced to deviate to find a portfolio that satisfies this constraint.

These illustrative examples show how one can simply model the incorporation of an alternative objective into portfolio optimization. This outcome can be achieved by changing the expected return forecast for a stock or simply adding the term into the objective function with a prespecified parameter. As shown in Exhibit 2, both the 2D and 3D approaches that target a minimum 40% CTL improvement achieve this objective consistently over time. The 3D approach, however, exhibits greater variability in its CTL profile, occasionally exceeding the 40% minimum by a significant margin, because the 3D approach allows the optimizer to prioritize CTL improvement more heavily when it is expected to be beneficial from a risk–return perspective. The results presented in Exhibits 1 and 2 demonstrate the flexibility and effectiveness of the 3D investing framework in incorporating forward-looking climate metrics into the portfolio construction process.

It is important to note that the specific results presented here are based on a particular set of assumptions and data inputs and may not be representative of all scenarios. The appropriate trade-off between expected returns, risk, and climate alignment will depend on an investor's specific preferences, constraints, and investment horizon. Nevertheless, the 3D investing framework provides a useful tool for exploring these trade-offs in a systematic and transparent manner and can be adapted to incorporate a wide range of forward-looking climate metrics and optimization objectives.

Implications and Applications of 3D Investing for Net-Zero Portfolios

The CTL example is a simple application of the 3D investing framework of Blitz et al. (2024) but does not present anything new. Rather, it demonstrates how incorporating a simple forward-looking climate measure into the objective function is a trivial process, and the decision one must make concerns the relative risk–return cost of integrating this objective. Naturally, the question that someone using such a framework must answer is, What forward-looking climate measure do I want to target? This is a key challenge of the net-zero framework: The required forward-looking nature of both financing the transition and decarbonizing means that there is uncertainty around how to measure and model the required decarbonization pathway. Nevertheless, in this section, we elaborate on some of the implications of net zero for portfolio construction and present potential mechanisms for integrating net-zero goals into the portfolio construction problem.

Implications of Net Zero for Portfolio Construction

The transition to a net-zero economy has significant implications for portfolio construction because investors must navigate the complex trade-offs between achieving long-term climate goals and maintaining short-term financial performance. Traditional portfolio optimization frameworks, which focus solely on expected returns and risk, must be extended to handle the multi-objective nature of net-zero investing. One of the key challenges in constructing net-zero portfolios is balancing the need to reduce portfolio emissions in the short term with the objective of financing the transition to a low-carbon economy in the longer term. It requires investors to consider not only the current carbon footprint of their holdings but also the forward-looking emission trajectories and transition plans of the companies in which they invest.

The 3D investing framework provides a tool for navigating these trade-offs by allowing investors to explicitly incorporate both short-term emission reduction targets and long-term net-zero alignment objectives into the portfolio construction process. By including a term in the objective function that minimizes the portfolio's current carbon footprint, investors can ensure that their portfolios are aligned with the urgent need to reduce emissions in the near term. At the same time, by incorporating forward-looking metrics such as Implied Temperature Rise or transition readiness scores, investors can position their portfolios for the long-term transition to a net-zero economy. This forward-looking perspective is important for identifying companies that are well positioned to thrive in a low-carbon future and avoiding those with elevated risks of being left behind.

Another key implication of net-zero investing is the need to consider the real-world impact of portfolio allocation decisions. Although traditional portfolio optimization focuses solely on the financial outcomes for the investor, net-zero investing requires a broader perspective that considers the impact of investment decisions on the overall decarbonization of the economy. The 3D investing framework can accommodate this broader perspective by incorporating metrics that capture the alignment of portfolio companies with science-based emission reduction targets or the contribution of portfolio holdings to the financing of low-carbon solutions. By explicitly considering these real-world impact metrics alongside financial objectives, investors can ensure that their portfolios not only are aligned with net-zero goals but also support the transition to a low-carbon economy.

Constructing net-zero portfolios using a 3D investing framework presents some challenges, however. One key issue is the need to specify the relative weights of the various objectives in the optimization process, which can be a complex and subjective exercise. Investors must consider their own preferences and constraints when setting these weights, as well as the potential trade-offs between short-term and long-term objectives. Another challenge is the need for robust and reliable data on the emission trajectories and transition plans of portfolio companies. Although a growing number of companies are disclosing this information, the quality and comparability of these disclosures vary, making it difficult for investors to accurately assess the net-zero alignment of their portfolios. Naturally, any portfolio construction technique will grapple with similar challenges around data quality.

Despite these challenges, a 3D investing framework provides a valuable starting point for investors seeking to align their portfolios with net-zero objectives. By explicitly incorporating emission reduction targets and forward-looking transition metrics into the portfolio construction process, this approach enables investors to navigate the complex trade-offs between short-term and long-term objectives while also considering the real-world impact of their investment decisions. As the data and methodologies for net-zero investing continue to evolve, the 3D investing framework can serve as a foundation for further innovation and refinement in this critical area of sustainable finance. Although 3D investing provides a useful toolkit, investors face complex decisions around how to appropriately weight different objectives, which will require careful consideration of their specific constraints and objectives.

Incorporating Forward-Looking Net-Zero Metrics

Forward-looking metrics go beyond simple measures of current carbon footprint and aim to capture a company's alignment with future net-zero trajectories. By incorporating such forward-looking measures, investors can construct portfolios that may be better positioned for the transition to a low-carbon economy. The quality of the forward-looking measure and what it aims to capture specifically will influence the characteristics of any portfolio that integrates such a measure.

The climate traffic light we discussed is one example of a forward-looking climate metric. Investors may have a preference for other metrics, however, and our proposed framework accommodates any ordinal measure. The following are other examples of forward-looking net-zero metrics that could be integrated into a 3D investing framework:

- **Implied Temperature Rise:** This metric estimates the global temperature rise associated with a company's emission trajectory, providing an indication of its alignment with the Paris Agreement goals. A company with an Implied Temperature Rise below 2°C would be considered aligned with net-zero objectives.
- **Science-Based Targets initiative (SBTi) portfolio coverage:** This metric estimates the percentage of a portfolio's holdings that have set emission reduction targets validated by the SBTi as consistent with the Paris Agreement goals.
- **Transition readiness scores:** These scores assess a company's preparedness for the low-carbon transition based on such factors as its decarbonization strategy, capital allocation plans, and climate governance. Higher scores indicate better positioning for the net-zero transition.

To incorporate these metrics into a 3D investing framework, an investor could modify the objective function in Equation 2 as follows:

$$\lambda_1 \mathbf{w}'\boldsymbol{\mu} + \lambda_2 \mathbf{w}'\boldsymbol{\mu}_{ITR} + \lambda_3 \mathbf{w}'\boldsymbol{\mu}_{SBTi} + \lambda_4 \mathbf{w}'\boldsymbol{\mu}_{CTL} - \frac{\gamma}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w},$$

where $\boldsymbol{\mu}_{ITR}$, $\boldsymbol{\mu}_{SBTi}$, and $\boldsymbol{\mu}_{CTL}$ are vectors of the chosen forward-looking net-zero metrics for each asset. The λ_i parameters control the relative importance of each forward-looking metric alongside expected returns ($\boldsymbol{\mu}$) and risk (Σ) in the optimization process. The choice of values for the λ_i parameters will depend on an investor's specific net-zero goals and risk–return preferences. One approach could be to set these weights based on each metric's perceived importance and potential financial materiality. Alternatively, investors could use optimization techniques to identify the combination of weights that best aligns with their overall objectives, subject to tracking error and other constraints. As with any optimization input, sensitivity analysis will be important to understanding the impact of these choices.

By incorporating forward-looking net-zero metrics in this way, the 3D investing framework allows investors to construct portfolios that are not only aligned with current carbon reduction goals but also positioned for the long-term transition to net zero. This forward-looking perspective is crucial for investors seeking to manage the risks and opportunities associated with the low-carbon transition while still achieving their financial objectives.

Implementing Net-Zero Pathways

The 3D investing framework can also be used to construct portfolios that align with specific net-zero emission pathways or glidepaths over time. For instance, an investor could modify Equation 2 to include an additional constraint: $E_{actual}(t) \leq E_{target}(t)$, where $E_{actual}(t)$ is the portfolio emissions at time t and $E_{target}(t)$ is the target emissions level at time t prescribed by a net-zero pathway. The 3D optimization would then produce the portfolio that maximizes alpha and sustainability objectives and minimizes risk while also satisfying the net-zero glide path constraint. This approach ensures alignment with a long-term net-zero trajectory while allowing time-varying exposures based on expected returns and sustainability characteristics. Such a constraint could also trivially be added to any portfolio optimization problem and is not unique to a multi-objective framework.

Bolton et al. (2022) demonstrate how it is possible to achieve a net-zero portfolio that tracks major indexes[7] with limited tracking error, even if the underlying reference benchmark's carbon emission stays at the 2020 level. The authors did not consider the potential for alpha generation in such a portfolio. We use their portfolio construction as a starting point but now consider how one may incorporate alpha considerations in such a portfolio.

Following Bolton et al. (2022), we consider the total cumulative carbon budget of 268.5 gigatons (Gt) of carbon dioxide (CO_2) as of 2021 to meet the 1.5°C target by 2050. With this starting point of total emission, different pathways to the 1.5°C target exist, dependent on both the start date and level of decarbonization.[8] Regardless of the pathway chosen, we define the following:

- The net-zero investor's chosen target pathway portfolio emission at year t is $E_{target}(t)$.
- The actual portfolio emission at year t is $E_{actual}(t)$.
- The cumulative target pathway emission as of year t is $C_{target}(t) = \sum_{i=0}^{t} E_{target}(i)$.
- The cumulative actual emission as of year t is $C_{actual}(t) = \sum_{i=0}^{t} E_{actual}(i)$.

[7]Bolton et al. (2022) considered the MSCI All Country World, MSCI Europe, and MSCI Emerging Markets indexes.

[8]Bolton et al. (2022) explicitly state "starting in 2021, with a geometrical rate of emission reduction, the path can be either an immediate 25% reduction in carbon footprint, followed by an 85% decrease, or a constant annual 10% reduction. With a linear rate, the pathway can be either a 25% initial reduction, followed by an annual 3.2% reduction, or a constant annual 4.6% reduction. All these paths are structured so that the entire carbon budget of 268.5 Gt CO_2 is spent."

The problem of jointly optimizing alpha and risk and satisfying a net-zero path becomes

$$\max_{\mathbf{w}} \ \lambda \mathbf{w}'\boldsymbol{\mu} + (1-\lambda)E^{-1}_{actual}(t) - \frac{\gamma}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w}, \\ s.t.\ \mathbf{w}'\mathbf{e} = 1, \mathbf{w} \in \Omega, C_{actual}(t) \le C_{target}(t). \tag{4}$$

The objective function in Equation 4 is set up to jointly optimize alpha, risk, and actual annual carbon emission. The objective function will aim to minimize the actual carbon emission, but it is allowed to go *above* the target pathway emission, $E_{target}(t)$, if doing so will yield more attractive expected return or risk profiles. At the same time, the cumulative actual emission, $C_{actual}(t)$, is constrained to stay below the target pathway emission, $C_{target}(t)$, at each point in time. That is to say, the optimization problem will allow the actual annual emission to go above the target pathway annual emission only if there have been excess emissions "saved up" in previous years. We know that there is a temporal dimension to the impact of emissions on climate change (see Daniel et al. 2019; Fearnside et al. 2000). A ton of CO_2 does more damage to climate if released into the atmosphere now compared with the same ton of CO_2 released into the atmosphere later, all else equal. This means that with the constraint $C_{actual}(t) \le C_{target}(t)$, the optimized portfolio will strictly follow a net-zero path presented in Bolton et al. (2022) while jointly optimizing the immediate alpha, risk, and emissions considerations.

This formulation also has some limitations. One key drawback is that it requires specifying the net-zero pathway, $C_{target}(t)$, *ex ante*, which may not be optimal if new information emerges over time that suggests a different pathway would be more appropriate. Additionally, the use of a hard cumulative emission constraint may lead to suboptimal portfolios in some cases because it does not allow for any trade-off between emissions and other objectives once the constraint is binding. Thus, there is an element of path dependency, which any portfolio construction approach targeting a pathway will be exposed to. It is important to understand the implications of such constraints on the risk and return objectives.

To address these limitations, investors could consider several extensions to the formulation in Equation 4. For example, the cumulative emission constraint could be complemented with a penalty term in the objective function that imposes a cost on deviations from the target pathway. This situation could allow for a more flexible trade-off between current emissions, cumulative emissions, and other objectives while still ensuring alignment with the net-zero pathway.

It is important to note that the emission pathway constraint in Equation 4 operates independently of any other sustainability metrics in the objective function. In some cases, these objectives may be in tension—for example, favoring companies with strong transition plans could lead to short-term deviations from the desired pathway. Investors will need to carefully balance these considerations and may wish to fine-tune the relative weights in the objective function over time as new information becomes available. The 3D framework provides the flexibility to explore this balance, but the onus remains on investors to define their priorities and manage these trade-offs.

Finally, although a 3D investing framework provides a conceptual toolkit for navigating the complexities of net-zero portfolio construction, its practical implementation (and that of any portfolio construction approach) depends on the availability of high-quality, consistent, and comprehensive data. Investors seeking to incorporate forward-looking metrics such as Implied Temperature Rise, science-based targets, and transition readiness into their portfolio optimization face continuing data challenges. Many companies still do not disclose their full Scope 1, 2, and 3 emissions, let alone more granular information on their decarbonization strategies and capital allocation plans. Even among firms that do report this information, many methodologies and metrics lack standardization, making comparisons difficult. Moreover, the reliability of self-reported data can be questionable, highlighting the need for more robust auditing and verification processes. An important area is the continued development of comprehensive, standardized, and reliable datasets on corporate climate performance and risk management. Progress on this front will require a concerted effort from regulators, standard setters, investors, and companies to improve the quality and comparability of climate-related disclosures.

Conclusion

As the world grapples with the urgent need to decarbonize the global economy and achieve net-zero emissions by 2050, investors face the challenge of how to construct portfolios that align with these ambitious climate goals while still delivering on risk and return objectives. This chapter explores the value of the 3D investing framework as a tool for constructing net-zero-aligned portfolios. By explicitly incorporating sustainability metrics into the portfolio optimization objective function, 3D investing allows for dynamic trade-offs between expected returns, risk, and climate outcomes based on an investor's unique preferences and constraints. We show how the framework can be extended to incorporate forward-looking climate metrics and emission pathway constraints, enabling investors to pursue short-term decarbonization while preserving long-term alignment with net-zero targets. We also acknowledge, however, the inherent tensions in net-zero investing, such as balancing short-term performance with long-term climate goals, and the need for investor discretion in navigating these trade-offs.

Our analysis provides insights into applications of portfolio construction paradigms, but we recognize several limitations and areas for future research. A 3D net-zero investing framework must assume a forward-looking climate metric that captures the nuances of companies' decarbonization trajectories and potential contributions to real-world emission reductions. Future work could also explore how 3D investing could be adapted to optimize for climate impact beyond individual portfolio alignment, although quantifying this impact remains challenging.

Ultimately, translating these research insights into implementable net-zero investment solutions will require close collaboration between academics and practitioners. As climate goals evolve and data availability improves over time, investors will need to continually adapt and refine their approaches to net-zero portfolio construction. A 3D investing framework provides a framework for this ongoing innovation, offering the flexibility and rigor needed to face the challenge of aligning investment portfolios with the net-zero future.

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