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Integrating Forward-Looking Climate Metrics in Corporate Fixed-Income Portfolios

INTEGRATING FORWARD-LOOKING CLIMATE METRICS IN CORPORATE FIXED-INCOME INDEX PORTFOLIOS

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Existing climate investment approaches primarily incorporate screening or target backward-looking climate metrics, such as carbon intensity and brown revenues. In recent years, however, several forward-looking data metrics, such as temperature alignment and climate risk ratings, have become widely available. Investors that seek to manage risk and return from climate factors have increasingly expressed interest in these forward-looking metrics. While the effects of using such metrics in portfolio construction are understood in equity index universes, there remains a gap in understanding their effects in fixed-income index universes. We help fill this gap by analyzing the characteristics of forward-looking climate data metrics in commonly used fixed-income investment benchmarks, including the Global, US, and Europe investment grade (IG) and high yield corporations. In the Global IG USD universe, we also explore the effects of including these metrics on portfolio characteristics like diversification and tracking error. We then explore the effects of incorporating both forward-looking and backward-looking climate metrics on various representative portfolios.

Introduction

Investor allocation to climate-themed funds and strategies has increased sharply in recent years. Bioy, Wang, Pucci, and Biddappa (2024) study of global investment trends in climate funds identified a total of 1,506 mutual funds and exchange-traded funds (ETFs) as of December 2023, compared to fewer than 200 in 2018. Similarly, the assets under management (AUM) increased to about $540 billion in 2023, relative to about $40 billion in 2018. Although much interest has focused on equity strategies, fixed-income strategies accounted for about 13.5% of the AUM in climate-themed funds.

The drivers for investor interest in such strategies are manifold. Advances in scientific research—in particular, reports published periodically by the Intergovernmental Panel on Climate Change (IPCC), the International Energy

Agency (IEA), and the Network for Greening the Financial System (NGFS)—have highlighted the potential harmful impacts of climate change on global economies. Countries around the world have recognized the potential risks that climate change poses, resulting in international agreements to curtail the emissions of greenhouse gases (GHGs). Most notably, the Paris Agreement (signed in 2016) sets long-term goals to hold global temperature increase to well below 2°C above preindustrial levels and to pursue efforts to limit it to 1.5°C above preindustrial levels. More recently, countries represented at the 28th UN Climate Change Conference (COP28) at the end of 2023 reached an agreement to call on parties to triple renewables capacity and double energy efficiency improvements globally by 2030, while transitioning away from fossil fuels in a just, orderly, and equitable manner.[1] Similarly, global governmental policies and regulation have accelerated support for an energy transition, including the passage of the Inflation Reduction Act (IRA) in the United States in 2022 and the Net Zero Industry Act (NZIA) in the European Union (EU) in 2024.

Additionally, in recent years, investors with a variety of climate-related objectives (such as risk management, alpha generation, values alignment, or real-world impact) have signed on to various industry-led voluntary climate initiatives (for example, the Net-Zero Asset Owner Alliance, or NZAOA). The signatories to these voluntary initiatives are expected to adhere to certain requirements or, in certain cases, follow a net-zero framework. These frameworks include the Institutional Investors Group on Climate Change's Net Zero Investment Framework (IIGCC 2024b), the Science Based Targets initiative's framework for financial institutions (SBTi 2024), and the NZAOA's Target-Setting Protocol (NZAOA 2024). These frameworks, in turn, recommend that investors set targets broadly related to engagement (primarily with companies) and capital allocation within investment portfolios (portfolio decarbonization, climate solutions, etc.).

Another driver is the increased availability of company disclosures and data related to climate change. The Task Force on Climate-Related Financial Disclosures (TCFD) established voluntary guidance around effective disclosure of climate-related risks and opportunities by companies in various industries. This guidance framework has been adopted by several markets around the world, notably the United Kingdom, Singapore, and Hong Kong. In the EU, disclosure requirements, such as the Corporate Sustainability Reporting Directive (CSRD), will come into force in a phased manner over 2025–2027, whereas investment fund–related sustainability disclosures under the Sustainable Finance Disclosure Regulation (SFDR) have been in force since 2021. International efforts to standardize sustainability-related data have also accelerated in recent years, most notably with the establishment of the International Sustainability Standards Board (ISSB) under the International Financial Reporting Standards (IFRS) Foundation. The ISSB builds on work previously done by the TCFD and the Sustainability Accounting Standards Board (SASB), among others, and in 2023 released two sustainability standards

[1]See www.cop28.com/en/the-uae-consensus-foreword.

for companies (called IFRS S1 and IFRS S2). For investors, regulators in certain jurisdictions—for example, the United Kingdom[2] and Switzerland (State Secretariat for International Finance 2023)—encourage the disclosure of various climate-related metrics for investment portfolios, including forward-looking measures, such as the climate value at risk and implied temperature rise. Concurrent with these developments, climate- and sustainability-related data have become available from several third-party data vendors, such as MSCI, ISS ESG, S&P Trucost, and FTSE.

Company-level climate data are broadly classified into two main types: backward-looking data and forward-looking data. As the name suggests, backward-looking data refer to a company's activities in the past and cover such metrics as a company's carbon or GHG emissions, ownership of fossil-fuel reserves, revenues derived from fossil-fuel-related activities, and involvement in certain business activities. Such metrics have been available for several years and have an established data history, running five years or more. However, these backward-looking metrics may miss key information related to a company's future plans, innovation, or potential future risks and opportunities arising from climate change. Forward-looking metrics seek to measure such plans, risks, or opportunities and have recently become available in the market. These include such metrics as company emission reduction targets and temperature ratings, climate scenario–based "value at risk" estimates, and transition or physical risk ratings. We will cover these metrics in more detail in later sections.

For fixed-income investors, climate-related factors can be incorporated within their strategies in three main ways: screening-based approaches, green bonds, and tilts based on climate metrics. Previously, screening-based approaches (for example, based on business or product involvement screens) were the primary method, but in recent years, green bonds and tilts based on climate metrics have become more prominent. For instance, the EU adopted minimum standards for the Climate Transition Benchmarks (CTBs) and the Paris Aligned Benchmarks,[3] which set minimum requirements on business activity screens, portfolio-level carbon intensity and related annual improvements, and green-to-brown ratios, among others. We note that these regulatory benchmarks primarily focus on backward-looking climate elements, and recent investor-led guidance on net-zero benchmarks (IIGCC 2023; NZAOA 2022b) suggests an increased focus and preference for forward-looking elements. In this chapter, we seek to study the effects of incorporating such forward-looking climate data in fixed-income index universes.

The remainder of the chapter is organized as follows. In the next section, we provide an overview of existing literature and articulate the contribution of this chapter. Then, we describe the data used, including definitions, sources, and mapping procedures. In the subsequent section, we analyze the distribution in several universes, as well as the relationship between the metrics. Finally, we

[2]See www.handbook.fca.org.uk/handbook/ESG/2/3.html.

[3]See https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32020R1818.

analyze the impact of incorporating climate metrics in a global investment-grade universe and provide concluding remarks.

Literature Review

While interest in the body of research covering climate-related impacts on companies' financial performance and investment portfolio returns has increased in the years following the Paris Agreement, the area is still nascent and emerging in nature. This is very likely due to the short data history available (less than 10 years in most cases), generally low consistency among various datasets, and differing methodological approaches. As a result, the lessons in this literature review are appropriately caveated.

According to the TCFD (2017), companies may be impacted by climate change due to two main categories of risks and opportunities: those that are transition related and those that are physical related. Transition-related risks and opportunities could be driven by changes in government policy and regulation, litigation, development of new technologies, and changes in consumer behavior or preferences. Physical-related risks and opportunities are divided into chronic effects (e.g., temperature rise, sea level rise, precipitation) or acute effects (e.g., heatwaves, floods, cyclones).

The NGFS (2023, p. 12) examined the potential channels by which these transition and physical risks may be transmitted to the broader economy and the financial system. The study found climate change may affect businesses and households at the microeconomic level through property damage, loss of income, stranded assets, and so on, and at the macroeconomic level through shifts in prices, productivity changes, and socioeconomic changes, among others. These economic effects may, in turn, be transmitted to the financial system as, for example, credit risk (e.g., loan defaults), market risk (e.g., repricing of securities), or underwriting risk (e.g., insurance losses).

Institutional investors broadly consider these climate-related risks to be financially material, and some believe such risks are not fully priced (Krueger, Sautner, and Starks 2020). In the equity markets, several research articles have been published in recent years that try to tackle this question, with mixed results. For example, Bolton and Kacperczyk (2021, 2023) find a positive relationship between companies (US and global) with high emissions and expected returns, consistent with an interpretation that investors are demanding greater compensation for exposure to emission risk. However, Bauer, Huber, Rudebusch, and Wilms (2022) find that green stocks generally outperformed brown stocks over their study period in G7 countries. We note that these studies mainly focus on backward-looking data elements.

Beyond equities, Campiglio, Daumas, Monnin, and von Jagow (2023) conducted a broad literature study covering various asset classes and distinguished between research using backward-looking methodologies and forward-looking methodologies. We refer readers to the full study for a complete overview;

however, we highlight some of their key findings: (1) Climate-related risks may predominantly lead to negative effects on financial performance, (2) climate-related risks may not be fully reflected in asset prices, and (3) it is challenging to compare forward-looking methodologies due to heterogeneity in approaches and scope.

Several key studies focus on the fixed-income market. There is some evidence that green bonds may provide a hedge against transition and physical risks (Cepni, Demirer, and Rognone 2022). In the municipal bond market, counties that are more exposed to climate risks may pay more in underwriting fees and initial yields for long-term bonds (Painter 2020). Firms with poor environmental performance or high emissions may have lower credit ratings and higher yield spreads (Seltzer, Starks, and Zhu 2022) and may be perceived by the market as more likely to default (Capasso, Gianfrate, and Spinelli 2020). Further, Huynh and Xia (2021) find that bonds with a higher climate news beta may earn lower future returns. However, Mastouri, Mendirotta, and Giese (2022) suggest that although broader credit market and bond spreads do not yet incorporate potential climate risks, these risks may still have a material impact on the asset value of firms. Moreover, the magnitude of these risks can have an adverse impact on bond investors and other creditors.

Looking at physical risks, there is some evidence that firms exposed to higher sea-level rise pay a premium when issuing bonds (Allman 2022) and those in locations with higher climate exposure pay higher spreads on their bank loans (Javadi and Masum 2021).

Lastly, as it relates to forward-looking climate data in particular, there is some evidence that such metrics may contain information about future carbon emissions (Fang-Klingler, Stroh, and Wisser 2022). Additionally, firms with traditionally poor sustainability or climate performance (e.g., power generation, oil, and gas) may produce more and higher-quality green innovation (Cohen, Gurun, and Nguyen 2020). This finding further supports the idea that forward-looking metrics may capture information that is not contained in backward-looking data.

In addition, the practitioner literature on the incorporation of climate factors in investment management has evolved over the years. Andersson, Bolton, and Samama (2016) demonstrate the construction of reduced-carbon portfolios for passive equity investors at low levels of tracking error. Bender, Bridges, and Shah (2019) adopt a mitigation and adaption approach to equity index portfolios and demonstrate the incorporation of multiple climate metrics in the portfolio construction process. Kolle, Lohre, Radatz, and Rother (2022) construct climate-aware portfolios that also seek to harvest traditional return factors, such as value, momentum, and quality. More recently, Bender, He, and Sun (2024) study the incorporation of forward-looking climate metrics in equity index portfolios.

In addition to financial materiality and risk and return considerations, investors may have other drivers when considering the inclusion of climate-related factors in their investment strategies. These may include influencing real-world decarbonization, moral considerations, and reputation risk (NZAOA 2022a; Krueger et al. 2020). Studying the impacts of all the aforementioned drivers is out of scope for this paper, but we offer some views on the question of real-world decarbonization. Existing literature (Kölbel, Heeb, Paetzold, and Busch 2020) has outlined the main mechanisms of investor impact as (1) shareholder engagement (e.g., dialogue with company boards and management), (2) capital allocation decisions (e.g., shifting portfolio allocations toward greener companies), and (3) indirect impacts (e.g., endorsement and benchmarking). Making definitive conclusions is not possible due to the nascent area of study, but the findings suggest that the impact of engagement approaches is well supported while capital allocation approaches are only partially supported. More recent work (Quigley 2023) covering various asset classes suggests that investors may be able to have a higher degree of impact in fixed-income investments relative to equities; however, the volume and quality of supporting evidence is still low. Therefore, while it is theoretically possible for investors to influence real-world decarbonization by making investments in climate-aware strategies, this claim is uncertain, and further research needs to be conducted to verify and substantiate it.

In summary, the potential effects of climate change on the financial performance of companies and investment portfolios have been studied along many dimensions (transition versus physical, backward versus forward looking, return performance, equity index portfolio construction, loan spreads, bond yields, etc.). While equity index strategies that use climate metrics have been studied previously in the academic and practitioner literature, a gap in the research exists concerning the practical implications of incorporating forward-looking climate measures in corporate bond index universes. This chapter seeks to fill that gap.

Data Description

In this section, we describe the various datasets used in our analysis, including the climate-related metrics and benchmark index data.

Climate Metrics

In recent years, a variety of climate-related metrics have become available from public sources and third-party data vendors. These sources include the CDP, S&P Trucost, MSCI, ISS ESG, and Bloomberg. We refer readers to Bender et al. (2024) for a complete overview of such datasets and the lenses through which they can be interpreted. In summary, these metrics can be viewed as (1) decarbonization versus climate solutions, (2) mitigation versus adaptation, and (3) risks versus opportunities.

Without going into too much detail, in general, climate-related datasets are nascent and have relatively short data histories compared to company fundamental data. Data histories for forward-looking metrics in particular are even shorter, and methodologies are both complex and nonstandardized with wide variation among different data providers. In our study, we omit several underlying details of the metrics' calculation methodology, but we refer readers to Shakdwipee, Giese, and Nagy (2023) for an overview of the MSCI datasets.[4]

In our study, we use a combination of backward- and forward-looking climate data supplied by MSCI ESG Research and ISS ESG. Note that we do not differentiate between green and nongreen bonds that are issued by the same company. Therefore, green bonds are treated the same; the primary driver is a lack of security-specific data for green bonds. An overview of the various input metrics is provided in **Exhibit 1**. In the following subsections, we describe the various metrics we use in more detail.

Backward-Looking Climate Metrics

We utilize three commonly used backward-looking metrics: carbon intensity (CI), potential emissions (PE), and brown revenues (BR). Next, we describe these metrics.

Carbon Intensity (CI)

The GHG Protocol recommends standards for company-level Scope 1, Scope 2, and Scope 3 emissions. Data vendors collect emission data that are disclosed by companies via various methods (company sustainability reports, annual reports, CDP disclosures, etc.) and supplement these data with their own proprietary estimation models to improve coverage for wide investment universes.

- *Scope 1* emissions are direct emissions from sources that are owned or controlled by a company. They include, for example, on-site fossil-fuel combustion and fleet fuel consumption.
- *Scope 2* emissions are indirect emissions from sources that are owned or controlled by a company. They include emissions that result from the generation of electricity, heat, or steam purchased from a utility provider.
- *Scope 3* emissions are from sources not owned or directly controlled by a company that are nonetheless related to the company's activities or the use of its products. They include emissions generated by a company's nonelectricity supply chain, employee travel and commuting, and emissions associated with contracted solid waste disposal and wastewater treatment. Scope 3 is often divided into "upstream" and "downstream" emissions.

Although Scope 3 emissions can be a large part of a company's carbon footprint, there are several challenges associated with using these data for investment use cases (Fouret, Haalebos, Olesiewicz, Simmons, Jain, and Kooroshy 2024;

[4]An overview of the single ISS ESG dataset can be found at www.issgovernance.com/esg/climate-solutions/carbon-risk-rating/.

Exhibit 1. Overview of Climate Metrics Used in This Study (as of August 2024)

Metric Name	Abbr.	Definition	Units	Data Source	History Available	Range	Interpretation[a]
Carbon Intensity	CI	Scope 1 and Scope 2 emissions per $1 million revenue	Tons of CO_2 equivalent per $1 million	MSCI	2012	Positive values	Lower is better
Potential Emissions	PE	Potential emissions related to fossil-fuel reserve ownership	Million tons of CO_2 equivalent	MSCI	2017	Positive values	Lower is better
Brown Revenues	BR	Percentage of revenues derived from fossil-fuel-related activities	% of revenues	MSCI	2017	0%–100%	Lower is better
Implied Temperature Rise	ITR	The global temperature rise (in the year 2100) if the whole economy had the same carbon budget over-/undershoot level as the company analyzed	°C	MSCI	2022	1.3–10	Lower is better
Carbon Risk Rating	CRR	Rating that measures a company's preparedness for a low-carbon economy	NA	ISS ESG	2016	0–100	Higher is better
Policy Climate Value at Risk	Pol-CVaR	A company's aggregated downside policy risk exposure	% of market value	MSCI	2022	−100% to 0%	Higher (less negative) is better
Technology Climate Value at Risk	Tec-CVaR	A company's upside technology opportunity exposure	% of market value	MSCI	2022	0%–100%	Higher (more positive) is better
Physical Value at Risk	Phy-CVaR	A company's expected downside or upside potential from physical climate events	% of market value	MSCI	2022	−100% to 100%	Higher (less negative) is better

[a]The interpretation is provided for readers viewing these metrics from a risk/opportunity lens. For example, assuming CI as a proxy for climate risk, a lower value is better (considered to be less risky).

Sources: State Street Global Advisors; MSCI ESG Research; ISS ESG.

IIGCC 2024a). As a result, we use Scope 1 and Scope 2 emissions in our research. To make the metric comparable across companies of different sizes, we normalize the emission figures with a company's annual sales.

Potential Emissions (PE)

This metric is based on fossil-fuel reserves that are owned by companies and disclosed in their public reporting. PE sources can be various types of coal (metallurgical and thermal), oil (conventional, shale, or tar sands), and gas (natural or shale). MSCI provides proven and probable reserves (2P) for coal and proven reserves (1P) for oil and natural gas. In some cases, they also consider 2P values for oil and natural gas if a company does not disclose its 1P. The reserve values are then converted to equivalent potential carbon emissions estimated using various factors (net calorific value of the fuel, carbon content of the fuel, etc.), under the assumption that all reserves are combusted.

Brown Revenues (BR)

Similar to the PE metric, BR measure the proportion of revenues that a company derives in any given year from fossil-fuel-related sources and activities. These include fossil-fuel power generation, extraction, processing, transportation, and other supporting activities.

Forward-Looking Climate Metrics

We use three types of forward-looking metrics in our study: implied temperature rise (ITR), carbon risk rating (CRR), and climate value at risk (CVaR). CVaR is, in turn, divided into three components: policy, technology, and physical CVaR. Next, we describe these metrics.

Implied Temperature Rise (ITR)

Temperature alignment data for corporate issuers have become available in the sustainability data market in recent years. Companies around the world have started setting emission reduction targets over the past several years. According to the SBTi, as of 21 July 2024, over 8,500 companies have either set emission reduction targets validated by the SBTi or committed to do so.[5] In addition, companies may set targets voluntarily as well, without SBTi validation.

However, these emission targets vary widely in terms of target date, level of improvement, scope of emissions, and exact emission metric being targeted (economic intensity, physical intensity, or absolute emissions), among other factors. As a result, comparing such targets across companies can be quite challenging, especially when adding in considerations of regional and sectoral differences.

[5]See https://sciencebasedtargets.org/companies-taking-action.

Temperature alignment scores assess the myriad company emission reduction targets and assign companies a "temperature score," making them more easily comparable and interpretable. Such temperature scores are known by various names—for example, ITR, temperature alignment, and Paris alignment. We provide a brief overview of MSCI's methodology next.

Several steps are involved in the estimation of MSCI's ITR. First, companies are assigned a carbon budget based on the projections of the NGFS REMIND Net Zero 2050 scenario. Next, companies' future emissions are projected according to their stated targets and are adjusted based on a credibility assessment. Third, the company's projected emissions are compared with its carbon budget, and an overshoot or undershoot factor is calculated. Last, this over-/undershoot is converted into a temperature figure based on an estimated relationship between carbon emissions and temperature outcomes.

Note that such methodologies are inherently complex and involve several assumptions and modeling choices made by data vendors. In addition, calculation of ITR scores at the portfolio level is recommended to be done using an "aggregate budget method." We omit technical detail here and simply note that this measure differs from the weighted average method that is typically used to calculate portfolio-level statistics. In our analysis, we specify whether ITR calculations are presented using a portfolio-weighted average or an aggregate budget method, but in general, the takeaways do not differ materially when using either method.

Carbon Risk Rating (CRR)

The CRR is a climate transition risk assessment created by ISS ESG. It is composed of two main parts:

1. *Carbon Risk Classification*, which assesses a company's exposure to carbon-related transition risks by estimating its emission intensity in the company's value chain, based on its industry and business activities
2. *Carbon Performance Score*, which evaluates the current carbon-related performance of a company, as well as a company's risk management and measures to reduce its CI in the future

ISS ESG combines the two components and rescales such that each company can obtain a score between 0 and 100, where 0 is considered high risk (worst score) and 100 is considered low risk (best score). Effectively, the CRR is a metric that assigns a risk rating to every company based on its sector and business activities, as well as its efforts to manage potential transition risks.

Climate Value at Risk (CVaR)

MSCI's CVaR metric seeks to quantify the potential effects of climate change into a dollar value impact on a company's valuation, typically expressed as a percentage of company value at risk over a 15-year time horizon under various climate scenarios. MSCI calculates the CVaR for its coverage universe under a variety of climate scenarios (orderly transition, disorderly transition, hothouse world, and temperature outcomes ranging from 1.5°C to 3°C). The CVaR metric is also further broken down into three components: Policy CVaR (Pol-CVaR), Technology CVaR (Tec-CVaR), and Physical CVaR (Phy-CVaR). These loosely correlate to transition risks, transition opportunities, and physical risks.

Pol-CVaR is estimated by modeling the potential negative impacts to company financials under future policies (proxied using carbon prices) projected under various climate scenarios.

Tec-CVaR is estimated by modeling the potential positive impacts of low-carbon patents on company financials under various climate scenarios.

Phy-CVaR is estimated by modeling the potential positive or negative impacts of various physical climate events (extreme cold, extreme heat, extreme precipitation, heavy snowfall, extreme wind, coastal flooding, fluvial flooding, tropical cyclones, river low flow, and wildfires) under various climate scenarios.

In our study, we use CVaR estimates under the NGFS REMIND Net Zero 2050 scenario and examine each subcomponent separately.

Index Data

Indexes are selected by market participants for a variety of reasons, but the key features investors typically seek when choosing a benchmark include the breadth of the fixed-income market captured, standardization of an index's security inclusion/exclusion criteria, pricing transparency of the underlying holdings, supporting analytics available on portfolio management systems, and flexibility to disaggregate particular segments of the covered universe.

In this chapter, we study the climate data characteristics of the following six indexes:

- Bloomberg Global Investment Grade Corporate Aggregate Index (Global IG)
- Bloomberg Global Investment Grade Corporate USD Aggregate Index (Global IG USD)
- Bloomberg US Investment Grade Corporate Aggregate Index (US IG)
- Bloomberg Pan Euro Investment Grade Corporate Aggregate Index (EUR IG)
- Bloomberg US High Yield Corporate Aggregate Index (US HY)
- Bloomberg Pan-European High Yield Corporate Aggregate Index (EUR HY)

Note that portfolio analysis is conducted only for the Global IG USD. All data are as of 31 May 2024.

Exhibit 2. Descriptive Statistics for Corporate Bond Indexes (as of 31 May 2024)

	Global IG	Global IG USD	US IG	EUR IG	US HY	EUR HY
No. Securities	16,393	10,165	8,000	3,704	1,949	664
No. Issuers	2,484	1,803	969	791	750	285
Total Market Value ($ billions)	12,040.31	8,109.29	6,621.09	2,855.65	1,283.98	360.41
Option-Adjusted Duration (OAD)	5.97	6.55	6.92	4.51	3.19	2.85
Option-Adjusted Spread (OAS)	94.56	87.87	84.64	107.87	308.21	321.81
Yield to Worst	5.10	5.56	5.52	3.88	8.00	6.31
Index Rating Number	8.20	8.18	8.18	8.34	15.06	13.98

Sources: State Street Global Advisors; Bloomberg.

All holdings and index weight data are sourced from Bloomberg. Additionally, relevant fundamental indicators, such as yield to worst, option-adjusted spread, option-adjusted duration, sector classifications, and market capitalization, are also sourced from Bloomberg. Some descriptive data on these indexes are provided in **Exhibit 2**.

Mapping Index Data to Climate Metrics

Climate data providers typically provide identifiers, such as an International Securities Identification Number (ISIN) or a ticker, to reference the securities that they cover and provide climate data for. Often, however, even if a company issues many securities, only one such security is referenced by the climate data provider. In such instances and particularly in corporate bond universes, it can be challenging to map climate data because of poor identifier matching. To overcome this challenge, we use a company- or issuer-level identifier system provided by Bloomberg. We map ISINs to their issuer, as well as to the issuer's parent and ultimate parent using this system.

As the first step in our mapping process, we join our index holdings to climate metrics using the security-level ISINs supplied by the providers. Next, for securities that are not mapped, we use Bloomberg's issuer-level identifier to map climate data to our index universes. If data for a particular issuer are not available, we next consider data related to the parent company. If data are still not available, we consider data related to the ultimate parent company. If data are not available even after all these steps, then we assume data are not available for that security.

Data Distribution and Relationships

In this section, we study the characteristics of the climate-related metrics in our selected index universes, including coverage, descriptive statistics, sectoral distribution, and data relationships in various universes. We also provide a short overview of our approach to missing data treatment, which is necessary where full coverage is not available.

Coverage in Selected Index Universes

First, we provide coverage statistics for our chosen climate metrics in the aforementioned index investment universes. The statistics are provided along two dimensions—by number of securities and by index weight.

We make the following observations based on **Exhibit 3**:

- Coverage of the metric for PE appears to be poor; in reality, however, this is a quirk of the data. Given most companies do not own fossil-fuel reserves, these are reported as null even if the company is assessed for other metrics. In this case, it is more representative to consider the coverage of fossil fuels to be the same as that of CI and BR.
- Within investment-grade universes, coverage is strong for backward-looking metrics (over 90%), while it is a bit varied for forward-looking data. Among these, CRR and ITR have good coverage (over 85%), while that for CVaR metrics is slightly weaker across the board.
- Within high-yield universes, a similar trend is apparent vis-à-vis backward- versus forward-looking metrics; however, we observe that the coverage is weaker across all data points relative to investment-grade universes.
- Sustainability datasets tend to be based on public financial disclosures by companies; therefore, they overwhelmingly focus on publicly listed companies. The credit space is composed of both public and private companies, the latter of which are not subject to the same public disclosure reporting requirements. As a result, coverage of private companies (which form a meaningful proportion of the universe) tends to be poor in comparison.

Missing Data Treatment

While using climate data metrics for practical portfolio construction use cases, missing data can be treated in two main ways: (1) excluding securities that are not covered and (2) missing value imputation or gap filling. The main drawback with the first option is that it can lead to high tracking error impact due to blunt exclusion, and it is usually not the preferred approach in practice. A gap-filling approach is typically preferred; however, note that the selection of an optimal method can be a separate research study of its own. As a result, for this study, we use an approach based on the observation that climate data metrics typically

Exhibit 3. Coverage of Climate Metrics in Various Index Universes (as of 31 May 2024)

Metric	Global IG		Global IG USD		US IG		EUR IG		US HY		EUR HY	
	By Number	By Weight	By Number	By Weight	By Number	By Weight	By Number	By Weight	By Number	By Weight	By Number	By Weight
CI	90.2	93.0	95.8	97.4	91.6	94.5	93.3	94.5	75.8	74.7	73.3	74.1
PE	4.2	4.4	6.7	6.1	4.2	4.2	4.8	5.1	3.6	3.2	0.5	0.7
BR	90.2	93.0	95.8	97.4	91.6	94.5	93.3	94.5	75.8	74.7	73.3	74.1
ITR	87.2	91.2	93.2	95.8	89.5	93.4	90.8	92.7	72.8	71.5	67.0	67.7
CRR	79.7	85.0	85.3	89.5	84.0	89.2	85.4	87.0	63.4	62.5	62.0	62.9
Pol-CVaR	67.4	75.1	72.7	80.0	73.4	81.7	71.5	74.3	48.7	48.8	41.3	44.1
Tec-CVaR	67.4	75.1	72.7	80.0	73.4	81.7	71.5	74.3	48.7	48.8	41.3	44.1
Phy-CVaR	67.4	75.1	72.7	80.0	73.4	81.7	71.5	74.3	48.7	48.8	41.3	44.1

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

display a strong dependence on the economic sector a company operates in (see **Exhibit 6**). Second, given that most sustainability data are based on publicly listed companies and commonly used sector classifications differ between equity and fixed-income universes, we prioritize the NACE classification,[6] which is recommended under the EU's Climate Benchmark regulation and can be used for both types of asset classes. Therefore, we fill in missing values for our climate metrics using the medians calculated by (in order of availability) NACE sectors and Bloomberg Class 3 sectors. Hereafter, all statistics and inferences are presented using climate data that are "gap filled" by the process described here.

Descriptive Statistics

To better understand the climate data characteristics, we present descriptive statistics in the combined universe of Global IG, US HY, and EUR HY in **Exhibit 4**. To avoid multiple counting, this calculation is based on unique issuers in the index, rather than individual securities.

Exhibit 4. Descriptive Statistics of Climate Data in the Combined Global IG, US HY, and EUR HY Universe (as of 31 May 2024)

Statistics	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Count	3,519	3,519	3,519	3,519	3,519	3,519	3,519	3,519
Count (nonzero)	3,517	136	584	3,519	3,518	3,519	1,643	3,511
Mean	257.0	37.8	9.37	2.63	49.79	−15.03	2.17	−1.64
Std. Deviation	867.1	321.2	25.97	1.64	13.94	24.31	8.54	4.50
Kurtosis	168.69	186.06	6.25	9.68	0.47	4.85	62.38	196.82
Skewness	9.85	12.39	2.78	2.95	0.15	−2.32	7.12	−11.76
Min.	0.0	0.0	0.00	1.30	0.00	−100.00	0.00	−100.00
5%	0.8	0.0	0.00	1.30	26.00	−82.03	0.00	−5.10
25%	5.4	0.0	0.00	1.70	42.00	−18.53	0.00	−1.40
50%	28.7	0.0	0.00	2.20	49.00	−3.86	0.00	−0.61
75%	134.6	0.0	0.00	2.90	58.00	−0.90	0.14	−0.31
95%	1,051.5	0.0	95.46	5.80	73.00	−0.51	10.24	−0.06
Max.	22,680.8	7,415.2	100.00	10.00	100.00	−0.08	100.00	6.21

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

[6]According to Eurostat, "The 'statistical classification of economic activities' in the European Community, abbreviated as NACE, is the classification of economic activities in the EU. The term NACE is derived from the French title: Nomenclature statistique des activités économiques dans la Communauté européenne." See https://ec.europa.eu/eurostat/web/nace/overview.

We make the following observations:

- CI, PE, and BR are all significantly right-tailed metrics, with medians much lower than the 95th percentile and their respective maximums. Pol-CVaR and Phy-CVaR are both left-tailed.
- PE and BR are predominantly zero values, with a small proportion of nonzero values (about 4% of issuers and 16% of issuers, respectively). Similarly, Tec-CVaR is also dominated by zero values, although the proportion of nonzero values is higher (about 47%).
- CRR is the only metric that appears to be somewhat normally distributed; all the other metrics display nonnormality and a high degree of skewness.

In **Exhibit 5**, we look at the overall climate data scores for each of the selected index universes in our study. In general, the US IG and US HY have higher climate exposures in the majority of metrics considered here, relative to EUR IG and EUR HY. Additionally, relative to their investment-grade counterparts, the two high-yield universes (US HY and EUR HY) tend to have more exposure along some metrics (ITR, CRR, Pol-CVaR) while having lower or comparable exposure along some other metrics (PE, CI, Tec-CVaR).

Exhibit 5. Climate Data Scores for Selected Index Universes (as of 31 May 2024)

Metric	Global IG	Global IG USD	US IG	EUR IG	US HY	EUR HY
CI	181.07	241.25	247.96	95.75	223.30	104.24
PE	83.35	89.13	92.75	94.50	11.69	2.78
BR	8.8	9.5	10.7	5.6	12.5	2.3
ITR (weighted average)	2.41	2.51	2.47	2.32	2.93	2.31
ITR (agg. budget)	2.35	2.48	2.58	2.09	3.30	2.21
CRR	56.69	55.74	56.18	59.73	45.32	54.29
Pol-CVaR	−11.97	−11.87	−11.73	−12.75	−15.29	−13.83
Tec-CVaR	1.76	1.22	1.15	3.45	0.89	3.80
Phy-CVaR	−1.31	−1.30	−1.14	−1.38	−1.54	−1.40

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

Exhibit 6. Climate Metrics' Weighted Averages in Global IG by Bloomberg Class 3 Sector (as of 31 May 2024)

Bloomberg Class 3 Sector	Index Weight	No. of Securities	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Banking	26.5%	3,029	3.9	0.0	0.0	2.42	65.28	−0.67	0.00	−0.43
Basic Industry	2.9%	556	442.9	279.1	3.2	4.69	46.25	−46.78	5.52	−2.92
Brokerage, Asset Managers, Exchanges	1.6%	316	2.8	0.0	0.8	2.18	56.58	−0.75	0.12	−0.36
Capital Goods	4.9%	902	182.6	0.3	0.7	3.22	47.71	−13.01	3.44	−0.77
Communications	7.3%	951	28.0	1.8	0.0	1.66	65.60	−2.64	0.04	−1.07
Consumer Cyclical	7.9%	1,303	27.8	0.1	1.4	2.60	49.20	−16.55	0.82	−1.81
Consumer Non-Cyclical	13.4%	2,069	31.6	0.0	0.0	1.93	64.39	−5.48	0.13	−1.24
Electric Utility	7.1%	1,714	1,467.3	2.3	32.2	2.64	41.54	−36.16	8.60	−1.51
Energy	5.8%	951	401.2	1,267.4	92.7	3.15	28.24	−59.85	7.86	−3.55
Finance Companies	1.0%	206	7.2	0.0	0.0	2.99	45.18	−0.93	0.00	−6.15
Other Financials	1.4%	389	59.0	0.0	0.0	3.09	45.79	−1.58	0.11	−2.18
Other Industrials	0.6%	188	126.7	231.7	3.3	2.50	49.07	−10.04	2.29	−3.60
Insurance	5.9%	1,155	12.2	1.6	0.2	1.69	59.08	−1.75	0.00	−0.79
Natural Gas Utility	1.3%	325	497.4	8.4	63.0	1.98	43.15	−34.54	6.93	−1.87
Other Utility	0.6%	146	433.4	0.0	2.9	2.18	50.64	−28.61	22.50	−2.50
REITs	2.6%	703	66.7	0.0	0.0	2.40	54.52	−0.92	0.06	−1.03
Technology	6.4%	855	28.4	0.0	0.0	1.92	66.65	−2.37	0.38	−0.98
Transportation	2.9%	635	259.1	0.0	2.0	2.74	53.81	−19.56	0.84	−2.90

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

Sector Distributions

To better understand the distribution of climate data across sectors, we now present sector-weighted averages for the climate metrics within the broad Global IG universe (see Exhibit 6). We make the following observations:

- There is significant variation among sectors, and climate data tend to be concentrated in certain sectors.
- Notably, Electric Utility, Natural Gas Utility, Energy, and Basic Industry generally have high exposure to the climate metrics considered here but also tend to have greater opportunities as measured by Tec-CVaR, corroborating previous research (Cohen et al. 2020).
- Companies in the Other Utility sector also score well on Tec-CVaR but may still be exposed to higher Pol-CVaR on an aggregate basis.

Data Relationships

We now seek to understand the relationships between the various climate metrics we use.

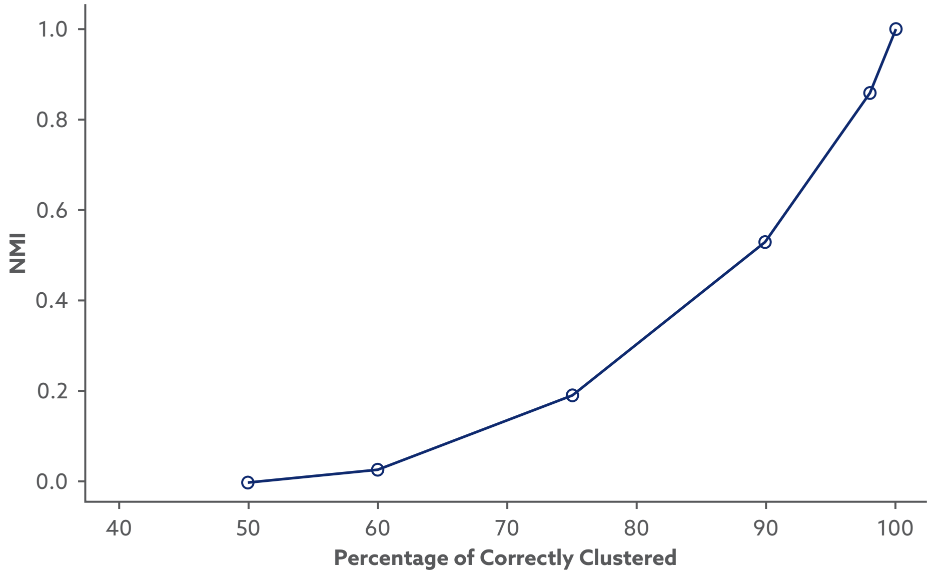
Methods

Pearson correlations are typically used to understand the linear correlations or relationships between datasets. As noted previously, however, climate metrics are quite concentrated and skewed (with the exception of CRR), making some relationships nonlinear in nature and challenging to understand and model. As a result, while correlation statistics for Global IG are reported in the appendix for the interested reader, we prefer to use alternative methods to understand the relationships. For this, we use the normalized mutual information (NMI) metric and decile-weighted averages.

The NMI is a clustering-based method that is commonly used to understand data relationships in machine learning applications and typically performs well at modeling nonlinear relationships. NMI can be interpreted as the decrease in uncertainty in X that results from knowing the value of Y. Details of the calculation methodology are provided in the appendix; however, we provide some helpful notes on interpretation of the metric, reproduced from Kachouie and Shutaywi (2020):

> NMI values close to one indicate that most of identified cluster labels agree with the true class labels. That is, most of the objects that belong to the same class are clustered in the same cluster. NMI value ranges from zero to one, but we should point out that it is a non-linear criterion for the clustering performance. For example, if in the clustering result, half of the data is correctly clustered, a linear criterion will score 0.5, while NMI score is zero. [**Exhibit 7**] shows NMI values with regard to

Exhibit 7. NMI Score versus Clustering Performance



Source: Kachouie and Shutaywi (2020).

clustering performance. It shows that NMI has a value of zero when 50% of the elements are correctly clustered, a value of about 0.5 when 88% of the elements are correctly clustered, a value of 0.6 when 93% of the elements are correctly clustered, and a value of one when 100% of the elements are correctly clustered.

In addition to the NMI, we also report decile-weighted averages by dividing the index universe into deciles based on selected climate metrics. We report these statistics as an additional robustness check; this method additionally accounts for index weights of various issuers, while the NMI weights all issuers equally.

Summary of Data Relationships

We first present our observations based on the NMI and decile calculations, and the detailed results are presented in the following two sections. We make the following observations:

- As may be expected, the three backward-looking metrics appear to have a relationship with each other: Companies with high CI also tend to have high BR or PE.
- CI also appears to be related to the forward-looking metrics: Companies with high CI also have poor CRR and Pol-CVaR. Interestingly, companies with high CI also tend to have higher Tec-CVaR, which further supports the findings from the sector analysis in the previous section.

- CRR and Pol-CVaR also appear to have a relationship with the backward-looking metrics. Companies that have high exposure to these two dimensions also have higher exposure to CI, PE, and BR. The relationship of these metrics with Tec-CVaR is also similar to that of CI: Higher-risk companies also have higher Tec-CVaR.
- Regarding ITR, the relationship among different metrics is weaker in comparison, although directionally similar.
- Phy-CVaR may have a weak relationship with Pol-CVaR and Tec-CVaR but not with the other metrics in consideration.

In summary, it appears that CRR and Pol-CVaR capture a lot of information contained in backward-looking data points, while ITR, Tec-CVaR, and Phy-CVaR appear to contain additional complementary information. In addition, these broad relationships appear to hold across the six universes we studied.

NMI Ratio

We present the NMI statistics in our selected index universes in **Exhibit 8**. Similar to before, these statistics are presented at the level of issuers rather than securities to avoid multiple counting.

Exhibit 8. NMI Ratio (as of 31 May 2024)

A. Global IG

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.41	0.01	0.24	0.25	0.34	0.03	0.02
BR	0.41	1.00	0.37	0.08	0.19	0.27	0.11	0.05
PE	0.01	0.37	1.00	0.18	0.41	0.42	0.15	0.10
ITR	0.24	0.08	0.18	1.00	0.07	0.07	0.07	0.05
CRR	0.25	0.19	0.41	0.07	1.00	0.15	0.11	0.09
Pol-CVaR	0.34	0.27	0.42	0.07	0.15	1.00	0.26	0.31
Tec-CVaR	0.03	0.11	0.15	0.07	0.11	0.26	1.00	0.05
Phy-CVaR	0.02	0.05	0.10	0.05	0.09	0.31	0.05	1.00

B. Global IG USD

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.44	0.01	0.26	0.23	0.37	0.02	0.02
BR	0.44	1.00	0.34	0.09	0.22	0.28	0.13	0.04
PE	0.01	0.34	1.00	0.19	0.38	0.39	0.13	0.06
ITR	0.26	0.09	0.19	1.00	0.07	0.09	0.10	0.06
CRR	0.23	0.22	0.38	0.07	1.00	0.18	0.10	0.10
Pol-CVaR	0.37	0.28	0.39	0.09	0.18	1.00	0.25	0.13
Tec-CVaR	0.02	0.13	0.13	0.10	0.10	0.25	1.00	0.07
Phy-CVaR	0.02	0.04	0.06	0.06	0.10	0.13	0.07	1.00

Exhibit 8. NMI Ratio (as of 31 May 2024) (*continued*)

C. US IG

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.46	0.01	0.27	0.16	0.39	0.04	0.02
BR	0.46	1.00	0.39	0.12	0.21	0.31	0.11	0.09
PE	0.01	0.39	1.00	0.26	0.46	0.39	0.21	0.16
ITR	0.27	0.12	0.26	1.00	0.08	0.09	0.12	0.07
CRR	0.16	0.21	0.46	0.08	1.00	0.16	0.11	0.09
Pol-CVaR	0.39	0.31	0.39	0.09	0.16	1.00	0.23	0.24
Tec-CVaR	0.04	0.11	0.21	0.12	0.11	0.23	1.00	0.11
Phy-CVaR	0.02	0.09	0.16	0.07	0.09	0.24	0.11	1.00

D. EUR IG

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.16	0.01	0.18	0.18	0.35	0.08	0.09
BR	0.16	1.00	0.45	0.06	0.26	0.39	0.14	0.12
PE	0.01	0.45	1.00	0.11	0.52	0.50	0.38	0.34
ITR	0.18	0.06	0.11	1.00	0.07	0.05	0.05	0.05
CRR	0.18	0.26	0.52	0.07	1.00	0.18	0.19	0.11
Pol-CVaR	0.35	0.39	0.50	0.05	0.18	1.00	0.37	0.29
Tec-CVaR	0.08	0.14	0.38	0.05	0.19	0.37	1.00	0.16
Phy-CVaR	0.09	0.12	0.34	0.05	0.11	0.29	0.16	1.00

E. US HY

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.15	0.06	0.20	0.12	0.32	0.04	0.01
BR	0.15	1.00	0.31	0.15	0.21	0.29	0.04	0.07
PE	0.06	0.31	1.00	0.41	0.33	0.38	0.01	0.00
ITR	0.20	0.15	0.41	1.00	0.07	0.14	0.08	0.14
CRR	0.12	0.21	0.33	0.07	1.00	0.11	0.07	0.07
Pol-CVaR	0.32	0.29	0.38	0.14	0.11	1.00	0.20	0.17
Tec-CVaR	0.04	0.04	0.01	0.08	0.07	0.20	1.00	0.07
Phy-CVaR	0.01	0.07	0.00	0.14	0.07	0.17	0.07	1.00

F. EUR HY

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.14	0.00	0.21	0.30	0.43	0.01	0.06
BR	0.14	1.00	0.86	0.20	0.20	0.34	0.01	0.02
PE	0.00	0.86	1.00	0.40	0.32	0.48	0.01	0.01
ITR	0.21	0.20	0.40	1.00	0.13	0.11	0.04	0.05
CRR	0.30	0.20	0.32	0.13	1.00	0.08	0.11	0.09
Pol-CVaR	0.43	0.34	0.48	0.11	0.08	1.00	0.35	0.17
Tec-CVaR	0.01	0.01	0.01	0.04	0.11	0.35	1.00	0.04
Phy-CVaR	0.06	0.02	0.01	0.05	0.09	0.17	0.04	1.00

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

Decile-Weighted Averages

We now present weighted averages by dividing the Global IG index universe into deciles based on ranking index constituents by a number of climate metrics (see **Exhibit 9**). Note that each decile is very close to but not exactly 10% of total weight. We do not present deciles based on PE, BR, and Tec-CVaR due to the low number of nonzero values available, meaning that decile comparisons are not sensible.

In our view, deciles are useful to examine because portfolio statistics are calculated based on index weights as a starting point and target portfolio-level-weighted average improvements for the most part (except for ITR), while also providing a robustness check for any observations made using correlations or NMI.

Exhibit 9. Weighted Averages within Deciles Created by Ranking Securities Based on Climate Metrics within the Global IG Universe (as of 31 May 2024)

A. Deciles Based on CI

Decile	Index Weight	No. Securities	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
1	10.0%	1,702	0.8	0.0	0.1	2.24	65.24	−1.60	0.03	−0.81
2	10.0%	1,421	2.2	0.0	0.0	1.92	63.30	−0.88	0.11	−0.51
3	10.0%	1,297	3.7	0.0	0.0	2.50	64.88	−1.79	0.04	−0.82
4	10.0%	1,183	5.8	0.7	0.0	2.24	62.88	−1.32	0.38	−0.49
5	10.0%	1,337	10.6	0.0	0.6	2.14	64.30	−3.09	0.18	−0.80
6	10.0%	1,588	20.6	0.8	0.5	2.49	54.35	−9.32	0.66	−1.95
7	10.0%	1,669	31.3	0.0	1.2	2.06	57.98	−7.50	0.93	−1.16
8	10.0%	2,044	63.0	57.0	4.6	2.29	52.14	−8.98	1.42	−1.75
9	10.0%	1,968	242.6	679.4	41.1	2.69	40.54	−41.48	8.02	−2.88
10	10.0%	2,184	1429.9	95.6	40.1	3.55	41.33	−43.74	5.86	−1.97

(*continued*)

Exhibit 9. Weighted Averages within Deciles Created by Ranking Securities Based on Climate Metrics within the Global IG Universe (as of 31 May 2024) (*continued*)

B. Deciles Based on ITR

Decile	Index Weight	No. Securities	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
1	10.0%	1,505	58.4	0.0	2.5	1.30	65.41	−7.29	3.30	−1.15
2	10.0%	1,514	51.8	0.0	2.6	1.45	64.92	−5.35	0.58	−0.88
3	10.0%	1,567	47.7	0.3	4.4	1.58	61.51	−5.96	0.86	−1.01
4	10.0%	1,851	63.3	1.0	3.7	1.75	59.13	−7.56	1.00	−1.16
5	10.0%	1,672	134.5	201.2	11.9	1.94	51.95	−15.14	2.80	−1.95
6	10.0%	1,679	76.0	107.8	6.1	2.13	55.19	−10.07	1.73	−0.99
7	10.0%	1,615	158.7	88.1	11.0	2.34	52.55	−13.69	1.37	−1.24
8	10.0%	1,477	178.2	81.0	12.7	2.63	55.34	−13.79	2.27	−1.40
9	10.0%	1,841	319.8	48.2	11.9	3.21	53.16	−13.25	0.94	−1.15
10	10.0%	1,672	722.2	305.7	21.4	5.81	47.75	−27.59	2.80	−2.22

C. Deciles Based on CRR

Decile	Index Weight	No. Securities	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
1	10.0%	1,301	22.6	0.0	0.3	1.70	79.53	−2.82	0.82	−1.13
2	10.0%	1,305	33.5	0.0	0.3	2.43	71.50	−2.63	0.15	−0.88
3	10.0%	1,351	10.3	0.0	0.0	1.97	67.66	−1.53	0.02	−0.60
4	10.0%	1,057	20.4	0.0	0.4	2.15	64.66	−1.84	0.12	−0.64
5	10.0%	1,491	89.1	0.0	2.1	2.34	61.99	−5.38	1.09	−0.86
6	10.0%	1,777	76.4	5.6	2.4	2.25	56.24	−5.29	1.00	−1.07
7	10.0%	2,036	89.8	5.7	1.3	2.60	51.11	−8.66	1.96	−0.96
8	10.0%	2,090	131.4	1.4	4.6	2.64	45.90	−14.30	2.59	−1.58
9	10.0%	2,069	727.7	4.2	25.4	3.00	40.33	−27.39	3.91	−2.72
10	10.0%	1,916	609.8	816.6	51.4	3.05	27.97	−49.87	6.00	−2.69

(*continued*)

Exhibit 9. Weighted Averages within Deciles Created by Ranking Securities Based on Climate Metrics within the Global IG Universe (as of 31 May 2024) (*continued*)

D. Deciles Based on Pol-CVaR

Decile	Index Weight	No. Securities	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
1	10.0%	1,278	7.0	0.0	0.0	2.22	66.06	−0.33	0.01	−0.39
2	10.0%	1,080	12.4	0.0	0.0	2.31	64.56	−0.58	0.01	−0.51
3	10.0%	1,427	5.9	0.0	0.0	2.15	63.14	−0.81	0.03	−0.44
4	10.0%	1,824	12.0	0.0	0.0	2.30	59.48	−0.91	0.01	−0.64
5	10.0%	1,672	24.2	0.0	0.0	1.91	62.47	−1.34	0.44	−1.58
6	10.0%	1,575	34.5	0.0	0.5	2.08	63.09	−2.61	0.44	−0.83
7	10.0%	1,634	42.0	2.1	2.8	2.20	60.07	−5.22	0.60	−1.31
8	10.0%	1,867	145.1	9.7	8.1	2.90	50.03	−11.41	1.83	−1.57
9	10.0%	2,302	872.2	18.5	29.6	2.67	43.21	−28.61	4.48	−2.53
10	10.0%	1,734	655.7	803.7	47.3	3.39	34.80	−67.91	9.80	−3.33

E. Deciles Based on Phy-CVaR

Decile	Index Weight	No. Securities	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
1	10.0%	1,511	123.7	38.7	4.5	2.21	61.56	−4.87	0.88	0.05
2	10.0%	1,385	70.7	0.0	1.4	2.62	61.54	−2.68	0.62	−0.20
3	10.0%	1,594	18.0	0.0	0.1	2.07	61.44	−1.22	0.07	−0.30
4	10.0%	1,422	36.5	0.4	1.6	2.27	61.02	−2.91	0.17	−0.34
5	10.0%	1,662	120.4	2.6	3.4	2.69	55.96	−5.12	0.87	−0.48
6	10.0%	1,814	87.3	56.5	5.0	2.18	59.96	−6.71	0.85	−0.65
7	10.0%	1,515	132.1	32.5	5.6	2.48	54.01	−13.76	1.73	−0.88
8	10.0%	2,111	802.1	55.8	24.7	2.62	49.75	−24.82	3.53	−1.23
9	10.0%	1,694	177.0	96.2	14.2	2.45	54.39	−21.54	1.06	−2.32
10	10.0%	1,685	242.8	551.0	27.8	2.55	47.29	−36.10	7.85	−6.79

Note: The deciles are created for each metric by ranking securities based on perceived risk exposure (low risk = Decile 1; high risk = Decile 10).

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

Portfolio Analysis

In this section, we restrict our analysis to the Global IG USD universe for three main reasons: (1) We want to maintain a global universe but remove the effects of currency, (2) the findings are generalizable to other regional-focused universes, and (3) coverage is marginally better relative to other universes studied (e.g., Global High Yield) and hence minimizes any impact from missing value treatments.

Portfolio Construction Approach

In order to construct portfolios that seek to improve the climate profile relative to the index, we chose to select simple portfolio-weighted averages as the target metric (except for ITR, which we will explain). Securities are ranked based on the target metric (e.g., CI), and the companies scoring the worst are screened out one by one (weight is reallocated to the remaining names proportionally) until the target objective is achieved (e.g., 20% reduction in weighted average CI). For ITR, a similar approach is followed; however, the target objective is calculated using the aggregated budget method (rather than weighted average). When multiple securities are tied, we screen out the one with the lowest index weight first and proceed as before. We construct the following portfolios and note that there is a certain level of subjectivity to choosing the level of improvements for various targets; however, we believe that the range in **Exhibit 10** covers commonly used targets by investors seeking to incorporate climate-themed investment objectives into their portfolios.

Exhibit 10. Details of Portfolio Target Metrics and Objectives Relative to the Standard Market-Capitalization-Weighted Index

Target Metric	Calc. Method	Target Type	Target Objective				
CI	Weighted average	Relative reduction	−20%	−40%	−60%	−80%	
PE	Weighted average	Relative reduction	−20%	−40%	−60%	−80%	−100%
BR	Weighted average	Relative reduction	−20%	−40%	−60%	−80%	−100%
ITR	Aggregated budget	Absolute level target (°C)	2.25	2.00	1.75	1.50	
CRR	Weighted average	Relative improvement	10%	20%	30%		
Pol-CVaR	Weighted average	Relative reduction	−20%	−40%	−60%	−80%	
Tec-CVaR	Weighted average	Relative improvement	10%	20%	30%	40%	
Phy-CVaR	Weighted average	Relative reduction	−20%	−40%	−60%	−80%	

For simplicity, the data presented in the following section include only the weighted average ITR; however, the interpretation and directionality are quite similar regardless of the approach selected.

We use this simple approach since we are constructing portfolios based on a single target metric. When there are a large number of sustainability objectives to consider in a portfolio's construction, an optimizer may be used to define the initial eligible opportunity set from which the portfolio will then seek to replicate. We do not explore this approach in our study, but it may be a suitable topic for future study.

For the construction of portfolios holding physical bonds, due to the large number of securities in broad credit market indexes, liquidity characteristics and transaction costs may render full replication of the index either impossible or not economically attractive. Hence, almost all credit strategies that cannot be fully replicated will usually be managed based on an approach called stratified sampling. We do not explain this approach further, but note that the impact of climate metric incorporation in practical portfolio management may have a slight difference relative to the research here. However, we believe the findings very much apply regardless.

Impact Analysis

In this section, we present the impacts of these sets of portfolios targeting improvement in a single climate metric along three dimensions.

Impact on Other Climate Metrics

First, in **Exhibit 11**, we demonstrate the effects on other climate metrics (e.g., portfolios that reduce CI are also studied for improvements in Pol-CVaR, PE, and all other metrics).

Exhibit 11. Improvements in Climate Metrics Relative to the Benchmark (as of 31 May 2024)

A. Portfolios Targeting Improvement in CI

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	−20%	−9%	−6%	−3%	1%	−4%	2%	2%
Portfolio 2	−40%	−8%	−12%	−4%	2%	−8%	−3%	2%
Portfolio 3	−60%	−6%	−20%	−5%	2%	−14%	−8%	2%
Portfolio 4	−80%	−13%	−45%	−9%	4%	−33%	−17%	−5%

B. Portfolios Targeting Improvement in Fossil-Fuel Reserves

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	7%	−31%	−4%	−1%	1%	−3%	6%	1%
Portfolio 2	7%	−42%	−6%	−2%	1%	−4%	6%	1%
Portfolio 3	7%	−61%	−10%	−2%	1%	−7%	−6%	0%
Portfolio 4	7%	−81%	−16%	−2%	2%	−11%	−18%	−2%
Portfolio 5	4%	−100%	−27%	−4%	3%	−19%	−19%	−4%

C. Portfolios Targeting Improvement in BR

	CI	FF	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	5%	−13%	−21%	−2%	1%	−5%	7%	0%
Portfolio 2	4%	−60%	−41%	−2%	3%	−14%	−3%	−3%
Portfolio 3	−7%	−90%	−60%	−5%	4%	−24%	−20%	−7%
Portfolio 4	−38%	−92%	−80%	−7%	5%	−32%	−26%	−7%
Portfolio 5	−70%	−99%	−100%	−8%	7%	−52%	−53%	−15%

D. Portfolios Targeting Improvement in ITR

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	−29%	−26%	−17%	−14%	2%	−16%	−5%	−9%
Portfolio 2	−45%	−52%	−35%	−20%	4%	−29%	−12%	−14%
Portfolio 3	−68%	−67%	−49%	−28%	5%	−36%	−21%	−15%
Portfolio 4	−72%	−95%	−57%	−32%	9%	−46%	−41%	−18%

(*continued*)

Exhibit 11. Improvements in Climate Metrics Relative to the Benchmark (as of 31 May 2024) (*continued*)

E. Portfolios Targeting Improvement in CRR

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	−64%	−99%	−78%	−8%	10%	−54%	−50%	−13%
Portfolio 2	−80%	−99%	−90%	−14%	20%	−74%	−75%	−33%
Portfolio 3	−88%	−100%	−98%	−19%	30%	−80%	−90%	−35%

F. Portfolios Targeting Improvement in Pol-CVaR

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	−6%	−52%	−15%	−4%	2%	−20%	−22%	−5%
Portfolio 2	−21%	−87%	−35%	−6%	4%	−40%	−35%	−8%
Portfolio 3	−64%	−95%	−56%	−10%	6%	−61%	−62%	−13%
Portfolio 4	−85%	−98%	−85%	−11%	10%	−80%	−82%	−29%

G. Portfolios Targeting Improvement in Tec-CVaR

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
Index level	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	9%	−1%	7%	−2%	0%	5%	16%	7%
Portfolio 2	15%	6%	11%	0%	−1%	9%	25%	11%
Portfolio 3	22%	7%	16%	1%	−2%	14%	35%	15%
Portfolio 4	31%	15%	25%	−1%	−4%	22%	44%	19%

H. Portfolios Targeting Improvement in Phy-CVaR

	CI	PE	BR	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
PORT_PCT	241.3	89.1	9.54%	2.51	55.74	−11.87	1.22	−1.30
Portfolio 1	8%	−11%	−3%	−2%	1%	−4%	2%	−20%
Portfolio 2	6%	−51%	−22%	−3%	2%	−16%	−20%	−40%
Portfolio 3	−5%	−71%	−33%	−4%	3%	−32%	−31%	−60%
Portfolio 4	−57%	−87%	−74%	−7%	7%	−68%	−65%	−80%

Notes: All statistics are reported using simple weighted averages. For Panel D, the ITR target by aggregated budget method is 2.25°C, 2°C, 1.75°C, and 1.5°C.

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

Portfolio Characteristics

Second, in **Exhibit 12**, we demonstrate the effects on fundamental portfolio characteristics, such as tracking error, duration, and yield.

Exhibit 12. Fundamental Portfolio Characteristics of Climate Improvement Portfolios (as of 31 May 2024)

A. Tracking Error

Tracking Error (in bps)					
Target	−20%	−40%	−60%	−80%	
CI	8.1	12.3	15.6	19.9	
Target	−20%	−40%	−60%	−80%	−100%
PE	5.2	5.0	6.2	7.1	9.0
Target	−20%	−40%	−60%	−80%	−100%
BR	6.3	8.7	11.8	15.5	31.3
Target	2.25	2	1.75	1.5	
ITR	9.0	7.4	17.7	37.4	
Target	10%	20%	30%		
CRR	17.6	24.0	38.4		
Target	−20%	−40%	−60%	−80%	
Pol-CVaR	9.7	12.2	19.8	25.4	
Target	10%	20%	30%	40%	
Tec-CVaR	9.4	16.4	13.1	16.1	
Target	−20%	−40%	−60%	−80%	
Phy-CVaR	4.0	6.4	10.6	49.9	

B. Option-Adjusted Duration

OAD (reference level = 6.55)					
Target	−20%	−40%	−60%	−80%	
CI	−1.0%	−1.6%	−2.1%	−2.7%	
Target	−20%	−40%	−60%	−80%	−100%
PE	−0.5%	−0.4%	−0.7%	−0.8%	−1.1%
Target	−20%	−40%	−60%	−80%	−100%
BR	−0.6%	−1.0%	−1.4%	−2.1%	−4.5%
Target	2.25	2	1.75	1.5	
ITR	−1.1%	−0.5%	2.0%	5.4%	
Target	10%	20%	30%		
CRR	−2.2%	−2.3%	3.1%		
Target	−20%	−40%	−60%	−80%	
Pol-CVaR	−1.3%	−1.7%	−2.7%	−3.3%	
Target	10%	20%	30%	40%	
Tec-CVaR	−0.7%	−1.7%	−0.4%	1.3%	
Target	−20%	−40%	−60%	−80%	
Phy-CVaR	−0.1%	−0.5%	−1.1%	−7.1%	

Exhibit 12. Fundamental Portfolio Characteristics of Climate Improvement Portfolios (as of 31 May 2024) (*continued*)

C. Option-Adjusted Spread

OAS (reference level = 87.87)					
Target	−20%	−40%	−60%	−80%	
CI	−0.6%	−0.6%	−0.9%	−2.0%	
Target	−20%	−40%	−60%	−80%	−100%
PE	−0.4%	−0.3%	−0.2%	−0.1%	−0.4%
Target	−20%	−40%	−60%	−80%	−100%
BR	−0.7%	−0.7%	−1.0%	−1.3%	−1.5%
Target	2.25	2	1.75	1.5	
ITR	−0.6%	−1.3%	−0.4%	−1.0%	
Target	10%	20%	30%		
CRR	−2.4%	−7.7%	−10.6%		
Target	−20%	40%	−60%	−80%	
Pol-CVaR	−0.5%	−0.8%	−1.4%	−2.8%	
Target	10%	20%	30%	40%	
Tec-CVaR	0.3%	0.9%	0.7%	0.1%	
Target	−20%	−40%	−60%	−80%	
Phy-CVaR	−0.7%	−0.7%	−1.0%	−1.9%	

D. Yield to Worst

Yield (reference level = 5.56)					
Target	−20%	−40%	−60%	−80%	
CI	−0.1%	−0.1%	−0.1%	−0.3%	
Target	−20%	−40%	−60%	−80%	−100%
PE	−0.1%	−0.1%	0.0%	0.0%	0.0%
Target	−20%	−40%	−60%	−80%	−100%
BR	−0.1%	−0.1%	−0.1%	−0.2%	−0.2%
Target	2.25	2	1.75	1.5	
ITR	−0.1%	−0.2%	0.0%	−0.2%	
Target	10%	20%	30%		
CRR	−0.4%	−1.2%	−1.6%		
Target	−20%	−40%	−60%	−80%	
Pol-CVaR	−0.1%	−0.1%	−0.2%	−0.4%	
Target	10%	20%	30%	40%	
Tec-CVaR	0.1%	0.2%	0.1%	0.0%	
Target	−20%	−40%	−60%	−80%	
Phy-CVaR	−0.1%	−0.1%	−0.2%	−0.2%	

Exhibit 12. Fundamental Portfolio Characteristics of Climate Improvement Portfolios (as of 31 May 2024) (*continued*)

E. Index Rating: Numeric Representation of Credit Ratings (AAA = 2, BAA3 = 11)

Index Rating (reference level = 8.18)					
Target	−20%	−40%	−60%	−80%	
CI	0.0%	0.2%	0.0%	−1.0%	
Target	−20%	−40%	−60%	−80%	−100%
PE	0.0%	0.0%	0.1%	0.3%	0.1%
Target	−20%	−40%	−60%	−80%	−100%
BR	−0.5%	−0.5%	−0.6%	−0.7%	−0.8%
Target	2.25	2	1.75	1.5	
ITR	−0.1%	−1.1%	−0.4%	−1.2%	
Target	10%	20%	30%		
CRR	−1.2%	−4.8%	−5.8%		
Target	−20%	−40%	−60%	−80%	
Pol-CVaR	0.0%	−0.4%	−0.6%	−2.0%	
Target	10%	20%	30%	40%	
Tec-CVaR	0.6%	0.6%	0.4%	0.9%	
Target	−20%	−40%	−60%	−80%	
Phy-CVaR	−0.3%	−0.4%	−0.9%	−3.4%	

Note: The tracking error statistics in Panel A represent *ex ante* one-year tracking error based on the Bloomberg MAC3 Model and are relative to the Global IG USD index.

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

Sector Weights

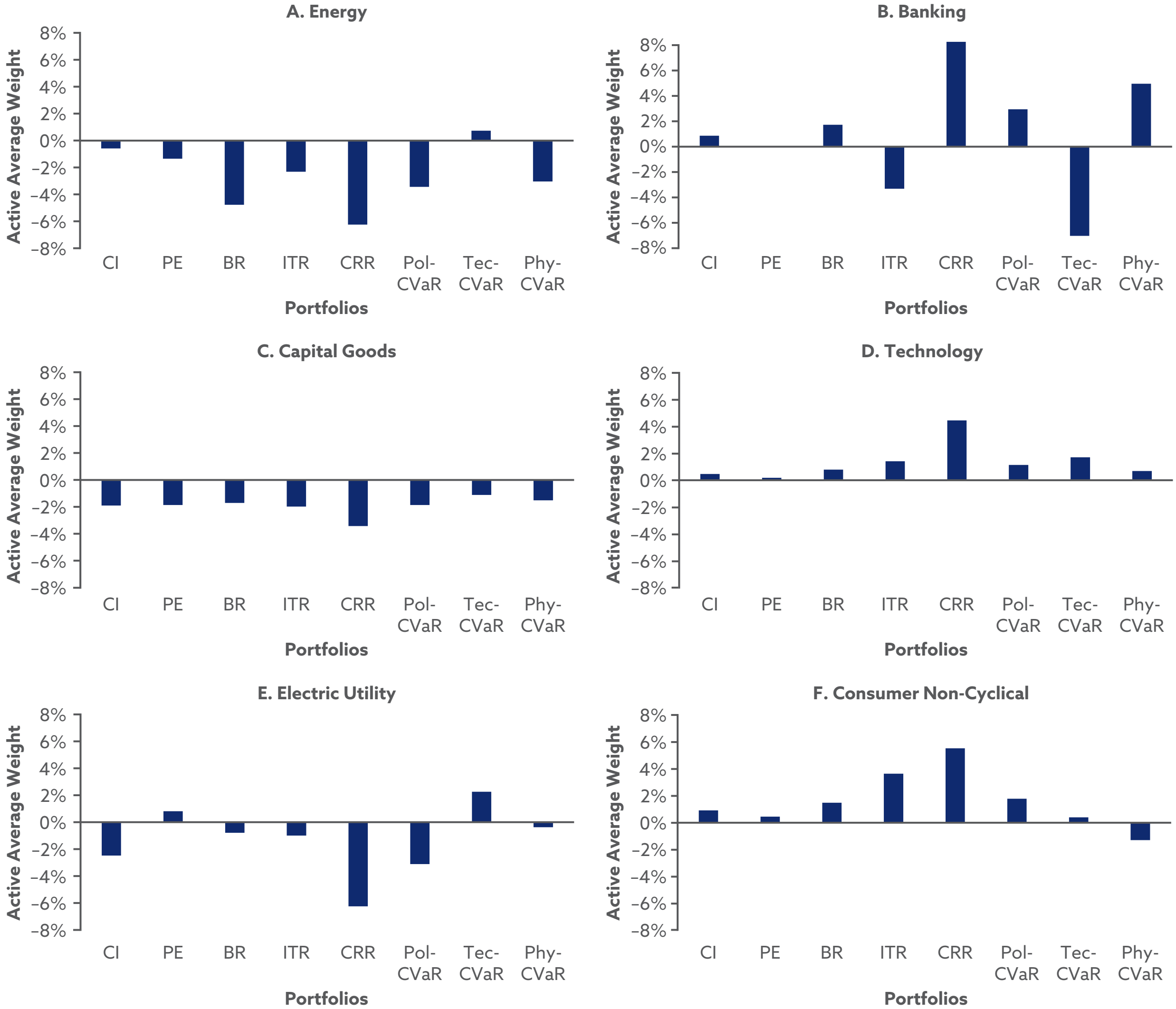
Third, we present the average active weights of certain sectors. The sectors are selected based on the average active weights across various metrics, as well as relative size in the index. For each target metric, we report the average active weight across the portfolios targeting improvement in that metric. For example, in Panel A of **Exhibit 13**, CI represents the average active weight to the Energy sector across the four CI improvement portfolios (−20%, −40%, −60%, and −80%).

Discussion

Based on the portfolios and analysis, we make several observations:

- It may be possible to target improvements in multiple metrics simultaneously without taking on too much additional risk. Due to the correlated nature of the underlying climate metrics, portfolios that target improvements in climate metric exposure also often result in improvements in other climate metrics. Notably, portfolios that target improvements in CI, PE, BR, ITR, or Pol-CVaR also concurrently result in improvement in the other metrics, though the level of improvement varies.

Exhibit 13. Average Active Sector Weights across Selected Sectors (Bloomberg Class 3; as of 31 May 2024)



Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

- However, a side effect of such portfolios is that they also result in a worsening of the exposure to the Tec-CVaR metric. This finding is further borne out by the results of the portfolios targeting an increase in Tec-CVaR, which results in a worsening for all the other climate metrics. This result indicates that it may be challenging to obtain simultaneous improvements in Tec-CVaR and the other metrics.
- An interesting finding is that improvement in CRR appears to improve the other metrics significantly as well (except for Tec-CVaR); however, this comes at the cost of a relatively higher tracking error and deviation in sector allocations.

- In general, the sector takeaways are not surprising and are consistent with previous research. Carbon-intensive sectors, such as Energy, Utilities, and Capital Goods, tend to be underweighted by such portfolios, while Banking, Technology, and Consumer Non-Cyclical tend to be overweighted. There does seem to be a nuance related to Tec-CVaR in which the effects appear to be reversed (underweights to Banking and overweights to Energy and Electric Utility).
- Regarding the *ex ante* tracking error impact of the portfolios that incorporate climate improvements versus the standard market-weighted index, in general, achieving higher improvement leads to higher tracking error. However, there does appear to be an "inflection point" for portfolio improvements in most metrics, where achieving the next level of improvement costs a lot more relative to the previous level. This is most visible for BR (moving from −80% to −100%), Phy-CVaR (going from −60% to −80%), ITR (going from 1.75°C to 1.5°C), and CRR (going from 20% to 30%). Regarding the level of tracking error itself, note that portfolios investing in investment-grade-rated bonds with *ex ante* tracking error above the 50 bp threshold are generally considered to be active investment strategies. For index investors in credit universes, the level of tracking error is typically constrained well below this threshold, and as a result, many of the portfolios we tested may prove to be impractical. Therefore, while small levels of improvement are possible at the lower end of the tracking error spectrum, larger and simultaneous improvements in the sustainability targets relative to the benchmark (particularly for Tec-CVaR) may prove to be challenging to achieve.
- Looking at the other portfolio characteristics, there are similar findings for the OAD, OAS, and index rating, while the impact on yield appears to be relatively muted.

Conclusion

Given the increasing prevalence and availability of forward-looking climate data metrics in investment management, we studied a selection of the various types of datasets available in the market. We found that coverage in common fixed-income universes is good in investment-grade credits but slightly lacking in high-yield universes, necessitating missing value treatments.

We found that although the classification would suggest otherwise, some types of forward- and backward-looking metrics are closely related to each other (notably, CI, PE, BR, ITR, and Pol-CVaR). At the same time, some forward-looking metrics (Phy-CVaR and Tec-CVaR) appear to have a weaker or an opposite relationship with backward-looking metrics and may contain complementary information.

We further found that portfolios that seek to improve against the index's climate profile may be able to achieve simultaneous improvements in multiple transition risk-related metrics while also losing exposure to transition opportunities. This finding suggests that the opportunity exposure may need to be controlled separately. We conclude by suggesting the study of simultaneous improvements in risk and opportunity as an area for future research.

Appendix

In this section, we review some key information theory concepts and provide Pearson correlation statistics of climate metrics in the Global IG universe.

Information Theory Concepts Review

In this section, we will use the entropy definition and notation from López de Prado (2018).

Let X be a discrete random variable that takes a value x from the set S_x with probability $p(x)$. The entropy of X is defined as

$$H(X) = -\sum_{x \in S_x} p(x) \ln[p(x)].$$

Throughout this section, we will follow the convention that $\ln(e) = 1$, $0 \ln(0) = 0$, since $\lim_{p \to 0^+} p \ln(p) = 0$. Entropy can be interpreted as the amount of uncertainty associated with X. Entropy is zero when all probability is concentrated in a single element of S_x. Entropy reaches a maximum at $\ln\left(\|S_x\|\right)$ when X is distributed uniformly, $p(x) = 1/\|S_x\|$, $\forall x \in S_x$.

Let Y be a discrete random variable that takes a value y from the set S_y with probability $p(y)$. The joined entropy of X and Y is defined as

$$H(X,Y) = -\sum_{x,y \in S_x \times S_y} p(x,y) \ln[p(x,y)].$$

Mutual information is defined as the decrease in uncertainty (or informational gain) in X that results from knowing the value of Y:

$$I(X,Y) = H(X) + H(Y) - H(X,Y).$$

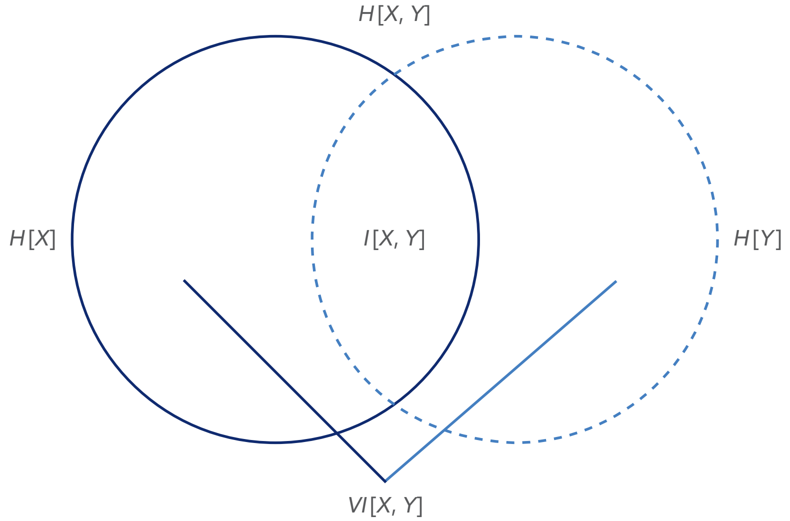
Variation of information is defined as

$$VI(X,Y) = H(X,Y) - I(X,Y).$$

It can be interpreted as the uncertainty one expects in one variable if told the value of other. **Exhibit A1** shows a pictorial depiction of these concepts.

It is important to recognize that that this definition of entropy is finite only for discrete random variables. In the continuous case, one can discretize the random variables. We adopt the methodologies from Hacine-Gharbi, Ravier, Harba, and Mohamadi (2012), Hacine-Gharbi and Ravier (2018), and López de Prado (2018).

Exhibit A1. Correspondence between Joint Entropy, Marginal Entropies, Mutual Information, and Variation of Information



Note: Readers familiar with these concepts will notice that the conditional entropies definition was not included to keep the graph clearer.

Pearson Correlation

For interested readers, **Exhibit A2** shows the Pearson correlation of climate metrics in the Global IG universe.

Exhibit A2. Pearson Correlation of Climate Metrics in Global IG (as of 31 May 2024)

	CI	BR	PE	ITR	CRR	Pol-CVaR	Tec-CVaR	Phy-CVaR
CI	1.00	0.39	0.00	0.38	−0.28	−0.42	0.11	−0.06
BR	0.39	1.00	0.34	0.23	−0.43	−0.48	0.17	−0.07
PE	0.00	0.34	1.00	0.09	−0.24	−0.33	0.17	−0.07
ITR	0.38	0.23	0.09	1.00	−0.27	−0.32	0.08	−0.08
CRR	−0.28	−0.43	−0.24	−0.27	1.00	0.46	−0.07	0.09
Pol-CVaR	−0.42	−0.48	−0.33	−0.32	0.46	1.00	−0.37	0.23
Tec-CVaR	0.11	0.17	0.17	0.08	−0.07	−0.37	1.00	−0.10
Phy-CVaR	−0.06	−0.07	−0.07	−0.08	0.09	0.23	−0.10	1.00

Sources: State Street Global Advisors; Bloomberg; MSCI ESG Research; ISS ESG.

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