ScientificPortfolio

Premium Indexing & Analytics — An EDHEC Venture

SPRING 2026

RESEARCH INSIGHTS EDHEC

EDHEC BUSINESS SCHOOL

Contents

Introduction

I am delighted to introduce the latest Scientific Portfolio special issue of the EDHEC Research Insights supplement to Investment & Pensions Europe (IPE). Here, we hope to provide institutional investors with insight on key issues in the industry today, focusing on areas where academic research and real-world implementation collide.

We first look at the ambition-credibility gap in corporate decarbonisation, seeking a new way of understanding whether companies are 'walking the talk' in relation to their own emissions targets. The findings strongly indicate that recent historical data and current/planned capital expenditure are not in line with companies' stated goals. The implications are significant for investors who are pursuing portfolio decarbonisation or alignment: we should avoid over-reliance on companies' professed targets when shaping strategy, tailor stakeholder engagement to prioritise real-world activity indicators, and press regulators to mandate relevant disclosures.

The subject of climate comes back into focus later in the supplement but, next, we turn to another timely challenge facing investors: equity return simulation. This is an old and problematic question for investment practitioners, but it has been receiving interesting new answers with the arrival of machine learning techniques. In our view, improvements in this field will be of particular importance to investors who are seeking to understand how portfolios perform in periods of macroeconomic stress, manage 'extreme risk', and more besides. Here, we propose an innovative hybrid methodology combining econometrics with generative neural networks ('GARCH in the machine') to produce more realistic simulated factor returns in a computationally feasible manner.

Third, we consider the subject of physical climate risk and explore a new way of quantifying climate physical loss (CPL). In two articles – addressing Europe and the US – we set out a methodology for calculating CPL that is parsimonious, aligned with the NGFS scenario set and directly applicable to portfolio construction thanks to its use of a discounted cash-flow model. We find that, while European countries on average exhibit lower macroeconomic sensitivity to physical climate risks than the US, we find that the European cap-weighted equity benchmark displays a larger CPL (–4.7%) than the US benchmark (–4.0%), due in part to its greater exposure to low-WACC (high cashflow-duration) sectors.

Finally, and perhaps importantly in a supplement that has a substantial focus on climate investing, we close with an examination of the 'hidden ethics' in the creation of climate alignment metrics. Although the sector strives for scientific methodological rigour, certain key decisions are irreducibly ethical in nature: we seek to identify those decisions and assess their relevance to measurement outcomes for a diversified portfolio of 1,300 stocks. Three 'ethical investor' archetypes are proposed, giving a framework through which an investor might establish clarity, consistency and transparency for their own ethical position.

We hope that the articles in the supplement will prove useful, informative and insightful. We wish you an enjoyable read and extend our warmest thanks to IPE for their collaboration on the supplement.

Shahyar Safaee, Deputy CEO and Director of Business Development, Scientific Portfolio

Printed by Senefelder Misset Doetinchem BV, The Netherlands.

Corporate decarbonisation and the 'ambition-credibility gap'

Vincent Bouchet, Director of ESG and Climate Research, Scientific Portfolio;
Alex Clark, Research Director, Asset Impact

Are companies 'walking the talk' on decarbonisation, or merely setting targets that they are not on track to achieve? Today, investors who are reshaping their own portfolios with emissions metrics in mind must form a view on the credibility of the decarbonisation activities of companies in which they invest – particularly those in climate-critical sectors that are responsible for the bulk of direct Scope 1 emissions. In this article (a summary of a recent research paper[1]), we examine this issue by comparing firms' decarbonisation targets with their real-world actions, including their recent historical emission trends and their current or planned capital expenditure activity. These trajectories are also benchmarked against the International Energy Agency's Net Zero Emissions scenarios for their sectors.

Key takeaways

There is a substantial gap between companies' stated expectations for emissions and their current direction of travel. The gap is particularly pronounced in absolute emissions, as many firms might reduce emission intensity while sustaining or expanding production.

Among eight climate-critical sectors, we find that misalignments are most severe in steel, oil and gas, shipping and aviation. Meanwhile, electricity and automotive display partial convergence with scenario pathways, although there is substantial dispersion among companies.

Based on this evidence, investors should ensure that their approach to long-term portfolio decarbonisation is not overly reliant on targets and consider anchoring stewardship strategies to real-world activity, including capex. We also encourage regulators to mandate standardised disclosure of historical trends and sector-specific physical indicators.

Introduction: the decarbonisation problem

For policymakers, corporate decarbonisation constitutes a key lever both for achieving Nationally Determined Contributions (NDCs) under the Paris Agreement and for establishing competitiveness across existing and emerging clean technologies. Firms contribute to national climate objectives through both their direct emissions and the downstream effects of their products and services, notably by decarbonising energy systems, industrial processes and transport infrastructures.

In parallel, investors – whose capital is indispensable to financing the low-carbon transition – are increasingly required to consider corporate emission-reduction targets in their investment decisions. In the European Union, this integration is encouraged through enhanced transparency obligations on the environmental performance of financial products (Regulation (EU) 2019/2088, the Sustainable Finance Disclosure Regulation), the classification of environmentally sustainable activities (Regulation (EU) 2020/852, the EU Taxonomy), and the introduction of climate benchmarks requiring explicit decarbonisation trajectories (Regulation (EU) 2019/2089, the EU Benchmark Regulation).

More recently, the European Banking Authority's (EBA's) near-final Pillar 3 disclosure framework on ESG risks has extended this logic to the banking sector. The framework mandates large credit institutions to disclose performance, exposure and impact indicators that quantify their financed emissions, sectoral exposures and the alignment of counter-

1 V. Bouchet and A. Clark (2025). Evaluating the Consistency of Companies Decarbonisation Targets in Critical Sectors.

parties' transition plans with reference to climate scenarios (EBA [2022]).

Despite these converging regulatory and market incentives, recent data indicates a widening gap between collective climate commitments and actual emission trajectories. Global greenhouse gas emissions reached 57.4bn tonnes of carbon dioxide-equivalent ($GtCO_2e$) in 2023 – a record high. To align with a 1.5°C pathway, emissions must decline by 42% by 2030 relative to 2019 levels. Yet, under current policies, 2030 emissions are still expected to be around 55$GtCO_2e$, even assuming full implementation of all unconditional NDCs. This trajectory would result in an estimated global average temperature rise of about 2.6–2.8°C by 2100, with profound consequences for the sustainability of human and non-human life. Expressed in cumulative terms, the remaining carbon budget consistent with a 50% probability of staying below 1.5 °C is now estimated at 200$GtCO_2e$, equivalent to approximately four years of current global emissions at current rates, while the 2°C budget amounts to about 900$GtCO_2$, corresponding to about 18 years (UNEP [2024]).

At the corporate level, a growing body of evidence reveals that announced net-zero pledges generally fall short of credible, science-based mitigation strategies. As shown by Hausfather and Peters (2021), corporate commitments tend to lack near-term milestones, rely excessively on future technological breakthroughs or offsets and omit disclosure of material Scope 3 emissions. Detailed analyses by Arnold and Toledano (2021) further indicate that among major emitters across seven hard-to-abate industries, fewer than half have set short-term emission-reduction targets, only one-third disclose absolute (rather than intensity-based) goals and barely 17% integrate decarbonisation criteria into capital-expenditure planning. Moreover, the widespread use of offsets and unverified carbon-capture strategies enable firms to appear on track toward 'net zero' without materially reducing their operational or value-chain emissions.

These shortcomings raise a central question: how credible are corporate decarbonisation targets when confronted with observable evidence on past performance and investment behaviour? How can we go beyond signals of intent and critically evaluate firms' mitigation strategies? Addressing this issue requires bridging the gap between corporate disclosure and real-economy indicators of transition readiness.

Table 1. Sectors covered in this analysis

Sector	Emissions (Scope)	Activity unit	No of companies	Share of global activity in sample
Oil and gas	CO_2e (1+2+3)	TJ	20	42%
Electricity	CO_2 (1)	kWh	20	15%
Cement	CO_2 (1)	t cement	20	25%
Steel	CO_2 (1+2)	t steel	20	26%
Aluminium	CO_2 (1+2)	t aluminium	20	48%
Automotive	CO_2 (3 downstream)	pkm	20	82%
Shipping	CO_2 (1)	tkm	20	43%
Airlines	CO_2 (1)	pkm	20	70%

Notes: Activity units are defined as follows – TJ (terajoules) denotes the quantity of energy produced (upstream oil and gas sector); kWh (kilowatt-hours) refers to electricity generated; t cement, t steel, t aluminium indicate one tonne of cement, crude steel and primary aluminium produced, respectively; pkm (passenger-kilometres) represents one passenger transported over one kilometre (automotive and airlines); tkm (tonne-kilometres) denotes one tonne of cargo transported over one kilometre (shipping).

A new approach to assessing alignment

In order to tackle this question, we established a multi-layered empirical framework to assess the consistency of corporate decarbonisation targets.

Company data and sample construction

Data for this analysis was obtained from four complementary sources. Firstly, historical absolute emissions were compiled using ISS data on reported emissions and Asset Impact company-level data, which is constructed bottom-up from asset-level capacity and activity (2019–23). Secondly, historical emissions intensities were obtained from Moody's and Asset Impact, expressed as emissions per unit of physical output.[2] Thirdly, target-based projections combined absolute-emission targets from ISS climate data with intensity trajectories from Moody's Temperature Alignment dataset, which extrapolates future intensities from stated reduction targets.

Finally, capex-based projections were produced by Asset Impact, including forward-looking asset-level capacity (retirements or additions), activity, technology choices and announced capital expenditures. For example, if a power generation utility sets a target of 6GW of new solar capacity by 2028, but the evidence shows only 2GW is under development by 2029, Asset Impact's projections reflect the latter figure and timeline, which is updated over time in response to updated information. Activity data is subsequently transformed into absolute emissions by applying models resolved at the asset level, then used to derive sector-level physical emissions intensities.

Scenario sector-specific benchmarks are derived from the International Energy Agency (IEA) Net Zero Emissions (NZE) by 2050 scenario, as presented in the World Energy Outlook 2024 (IEA [2024]). The NZE scenario charts a pathway to limiting global warming to 1.5°C, requiring global emissions to decline by roughly 45% by 2030 relative to 2010 levels. It specifies sectoral decarbonisation rates and technology deployment pathways across electricity generation, transport, industry and heavy materials, and serves as the reference point for assessing the ambition of corporate trajectories.

To construct appropriate samples, we looked at the 20 largest listed producers by sectoral output across eight carbon-intensive industries. The share of global production represented by these companies is detailed in table 1 and ranges from 15% (electricity) to 82% (automotive). This may well introduce a sample bias

2 Historical growth rates are computed as the compound annual growth rate over 2019–23. For historical series where both Asset Impact and Moody's/ISS data are available, a simple average of the two sources is used. Because Asset Impact's asset-based methodology and Moody's/ISS reporting-based approaches differ significantly in system boundaries, underlying assumptions, consolidation methodologies and coverage, absolute emission levels are not directly comparable. Consequently, this study focuses on emission trends (growth rates) rather than absolute values.

weighted towards larger companies: the purpose of this analysis is not to conduct robust statistical inference testing, nor are the source datasets suitable for this purpose given the differences in the approaches they use.[3]

Differences in trends between target-based, capex-based and historical projections were then evaluated using Wilcoxon signed-rank tests on paired firm-level observations. This non-parametric procedure is appropriate given the small to moderate sample sizes, the potential non-normal distributions of firm-level trend estimates and the natural pairing of methods within the same firm. Pairwise hypotheses were specified for each sector and metric (intensity and absolute): targets versus history, and targets versus investments. For each comparison, the null posits a zero median of the paired difference in trends.

Results: actions do not match intentions

Across the full sample, two consistent patterns emerge. First, target-based trajectories are systematically more ambitious than what has been delivered in the 2019–23 period. Second, and perhaps more concerning, capex-based trajectories are consistently less ambitious than targets, suggesting that current capital allocation is insufficient to deliver the announced reductions. This 'ambition-credibility gap' is evident across both absolute and intensity metrics (table 2a).

Interestingly, the gap grows even larger when we restrict the sample to companies with explicit targets. While target-setting firms might plan to decarbonise more rapidly than their peers, they are not allocating capital in a more consistent manner.

Statistical tests confirm that differences between historical, target-based and capex-based trajectories are significant at conventional levels across most sectors, particularly in intensity metrics.[4]

There is a considerable amount of dispersion between firms within each sector, indicating that sectoral averages conceal a wide diversity of individual firm behaviours.[5] Notably, the electricity and automotive sectors – two of the most aligned on average with transition objectives – also exhibit some of the greatest firm-level dispersion. This combination of apparent alignment and substantial heterogeneity highlights that aggregate progress may mask divergent firm-level pathways, calling for a granular and firm-specific assessment by investors when allocating capital within these sectors.

A closer look at sectors

The largest 'gaps': oil and gas, shipping, steel and aviation sectors

In the oil and gas sector, the IEA's net-zero pathway hinges on rapid operational abatement (cutting methane, ending routine flaring by 2030 and electrifying upstream operations) supported by carbon capture at processing and refining sites, together with a sizeable decline in oil and gas demand by 2030. In this framework, emissions intensity falls by approximately 7% and absolute emissions by approximately 24% over 2023–30. Relative to this benchmark, corporate targets reduce intensity and absolute emissions by about 5%, leaving 2030 outcomes above the scenario. Capex-based trajectories are markedly off-pace – intensity remains flat and absolute emissions rise by about 10% – while the continuation of recent history leaves intensity roughly flat but absolute emissions up by approximately 37%.

In shipping, the IEA's net-zero pathway combines stronger efficiency measures (design improvements, operational optimisation) with an early shift to low- and zero-emission fuels. In this context, emissions intensity falls by about 37% and

Table 2. Average trends by sector

a) All sample (160 firms)

Sector	Count	Absolute emissions			Intensity emissions		
		Target-based	Historical	Capex-based	Target-based	Historical	Capex-based
Airlines	20	-2.20%	7.60%	1.50%	-2.80%	-0.20%	-0.10%
Aluminium	20	-1.40%	5.50%	-0.80%	-5.10%	-1.70%	0.60%
Automotive	20	-4.20%	-2.90%	-3.70%	-4.30%	-4.40%	-4.60%
Cement	20	-1.20%	4.90%	0.40%	-2.10%	-0.40%	0.00%
Electricity	20	-4.00%	-3.60%	-2.00%	-8.00%	-2.60%	-2.70%
Oil and gas	20	-0.70%	4.60%	1.40%	-0.60%	-0.30%	0.00%
Shipping	20	-1.50%	0.50%	2.70%	-2.60%	-0.80%	0.60%
Steel	20	-1.10%	3.00%	1.30%	-2.60%	-1.40%	-0.30%
All universe	**160**	**-2.00%**	**2.50%**	**0.20%**	**-3.30%**	**-1.50%**	**-0.70%**

b) Companies with ambitious reduction targets (83 firms)

Sector	Count	Absolute emissions			Intensity emissions		
		Target-based	Historical	Capex-based	Target-based	Historical	Capex-based
Airlines	13	-3.40%	8.10%	1.60%	-3.70%	-0.80%	0.00%
Aluminium	10	-2.00%	0.00%	-0.30%	-5.20%	-2.00%	0.80%
Automotive	16	-4.80%	-3.30%	-4.90%	-5.00%	-3.00%	-5.20%
Cement	13	-1.60%	2.70%	0.60%	-2.30%	-0.60%	0.00%
Electricity	12	-6.60%	-4.40%	-3.80%	-9.20%	-3.50%	-3.60%
Oil and gas	6	-1.60%	1.30%	0.90%	-1.70%	-0.60%	0.20%
Shipping	5	-2.70%	-0.90%	2.30%	-4.40%	-0.90%	0.30%
Steel	8	-1.90%	3.30%	1.20%	-2.90%	-1.30%	0.00%
All universe	**83**	**-3.30%**	**0.80%**	**-0.80%**	**-4.50%**	**-1.80%**	**-1.30%**

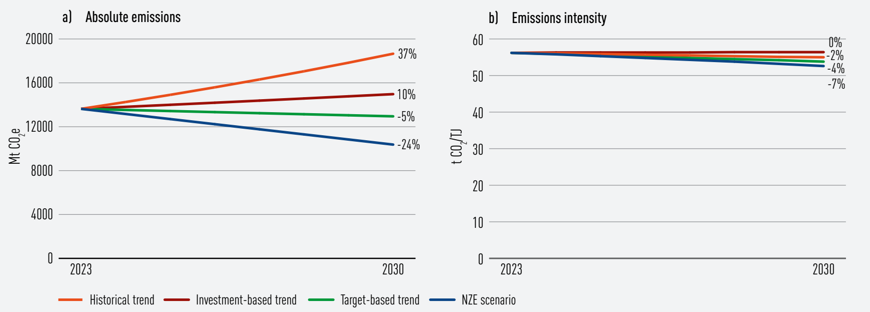
Notes: Target-based trends reflect annualised changes in emissions or emission intensities implied by companies' stated reduction targets. Historical trends correspond to observed compound annual growth rates over 2019–23 based on reported or asset-level emissions. Capex-based trends represent projected emissions trajectories derived from forward-looking asset capacities and capital expenditure, independent of stated climate pledges. Negative values indicate declining emissions, whereas positive values indicate increasing emissions.

3 For more detail on methodology, see V. Bouchet and A. Clark (2025). Evaluating the Consistency of Companies Decarbonisation Targets in Critical Sectors.

4 For statistical test results, see V. Bouchet and A. Clark (2025). Evaluating the Consistency of Companies Decarbonisation Targets in Critical Sectors.

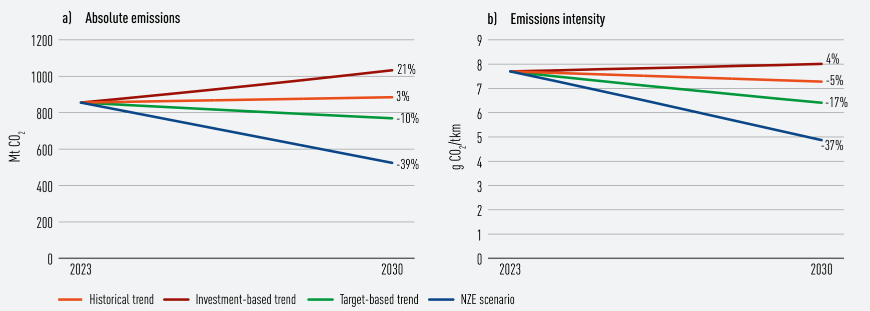
5 For dispersion data (interquartile ranges, standard deviations), see V. Bouchet and A. Clark (2025). Evaluating the Consistency of Companies Decarbonisation Targets in Critical Sectors.

Figure 1. Oil and gas



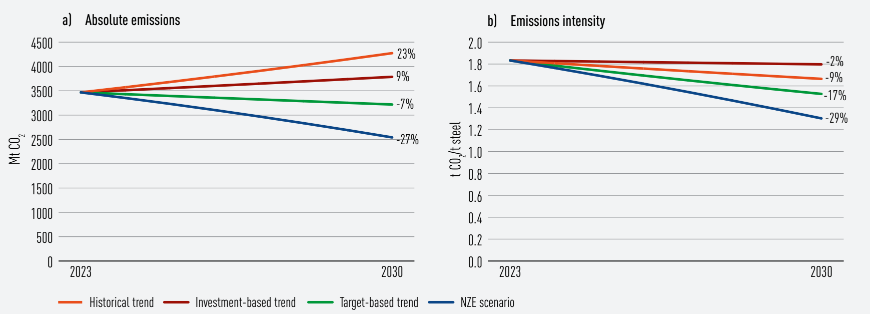
Notes: This figure presents, for the oil and gas sector, the trajectories of absolute emissions (Scope 1+2+3) and sectoral emissions intensity (tCO_2e/TJ) under alternative assumptions (Scope 2 emissions are estimated using the energy consumption from electricity of the sector and a global average grid factor, both from World Energy Outlook data). The starting point for both indicators is derived from the IEA World Energy Outlook 2024. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

Figure 2. Shipping



This figure presents, for the shipping sector, the trajectories of absolute emissions (Scope 1) and sectoral emissions intensity (gCO_2e/tkm – tonnes-kilometres) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

Figure 3. Steel



Notes: This figure presents, for the steel sector, the trajectories of absolute emissions (Scope 1+2) and sectoral emissions intensity (tCO_2e/t steel) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. Scope 2 emissions are estimated by combining electricity consumption data for the steel sector with a global average grid factor. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

absolute emissions by about 39% over 2023–30. Relative to this benchmark, corporate targets are far away on intensity and in absolute emissions. Capex-based trajectories also diverge sharply: intensity rises by roughly 4%, and absolute emissions by 21%, while the continuation of recent history leaves intensity down approximately 5% but absolute emissions up approximately 3%, both well above the scenario by 2030.

For the steel sector, the IEA net-zero pathway hinges on a rapid shift away from the conventional blast-furnace route toward lower emission production systems: a larger share of scrap-based electric-arc furnaces, early deployment of hydrogen-based direct-reduced iron that feeds electric-arc furnaces, application of carbon capture and storage to the remaining blast furnaces, and material efficiency measures that temper demand growth. Under this framework, emissions intensity declines by about 29% and absolute emissions by about 27% over 2023–30. Relative to this benchmark, corporate targets point to a drop in intensity of approximately 17% and of 7% in absolute emissions, leaving 2030 levels above the scenario. Capex-based projections diverge – intensity worsens by approximately 2% and absolute emissions rise by 9% – while a continuation of recent history leaves intensity down 9% but absolute emissions up 23%, well above the scenario by 2030.

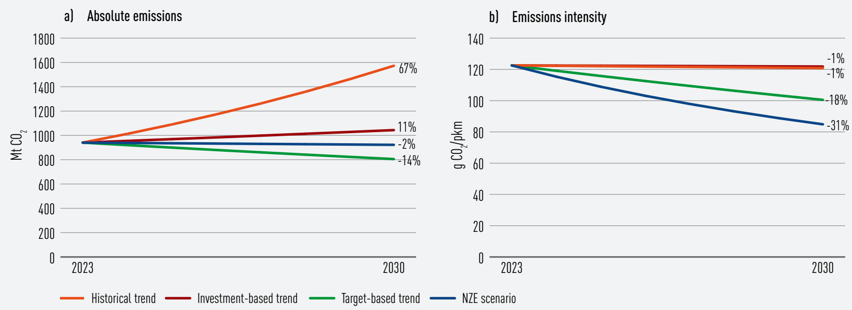
In aviation, the IEA anticipates substantial gains in emissions efficiency driven by advances in aircraft technology, improved engine performance, sustainable aviation fuels and enhanced operational practices. These improvements are expected to significantly reduce emissions per unit of output over the coming decades. Nevertheless, aggregate sectoral emissions are projected to remain broadly unchanged, as rising air traffic volumes offset the gains. Corporate decarbonisation targets in the airline industry exhibit a mixed degree of consistency with a net-zero pathway. On the one hand, the projected intensity trajectory implied by corporate targets is relatively close to the IEA scenario, suggesting that companies are broadly aligned with the technological and efficiency improvements required to decarbonise the sector on a per-unit basis. However, the comparison with recent historical trends reveals a stark contrast: intensity over the past has remained flat, and the continuation of such trends would place the sector far from the required trajectory. Moreover, an assessment based on current and planned investments suggests that emissions intensity should not improve in the future, reflecting insufficient capital allocation toward low-carbon technologies. When the focus shifts from intensity to absolute emissions, target-based trajectories are broadly consistent with, or even slightly more optimistic than, the scenario benchmark. By contrast, the extrapolation of historical performance and capex-based trajectories presents a markedly different picture, with absolute emissions projected to increase at a much faster pace than the scenario pathway.

Greater alignment? Automotive and electricity sectors

In the automotive sector, the IEA's NZE pathway is driven primarily by the rapid electrification of light-duty vehicles (electric models are expected to represent roughly two-thirds of global sales by 2030) alongside continued improvements in fuel efficiency for internal-combustion vehicles and additional gains from lightweighting and aerodynamics. These combined developments underpin a significant reduction in use-phase emissions, with emissions intensity projected to decline by more than 40% between 2023 and 2030 under the NZE scenario. Relative to this benchmark, corporate targets indicate a slower but still substantial reduction of around 25% – a pace that is broadly consistent with both capex-based and historical trajectories. In terms of absolute emissions, the NZE pathway implies a reduction of about 34% over the same period, compared with declines of roughly 25% under target-based and capex-based projections and around 20% under the continuation of historical trends. Overall, the automotive sector stands out as one of the few where targets, capital allocation and recent performance are broadly aligned, even if they remain slightly behind the trajectory required to meet a net-zero pathway. Nevertheless, the wide dispersion of firm-level trajectories within the sector (discussed above) underscores that this alignment reflects an average outcome rather than a uniform pattern, with some firms advancing much faster and others lagging behind the transition benchmark.

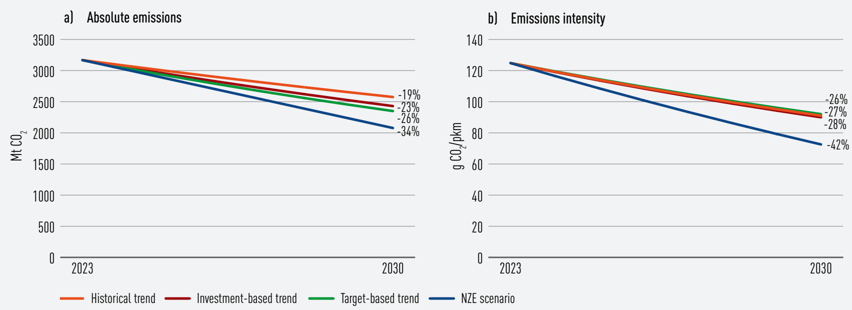
In electricity, the IEA's net-zero pathway hinges on a rapid system transformation: installed renewable

Figure 4. Aviation



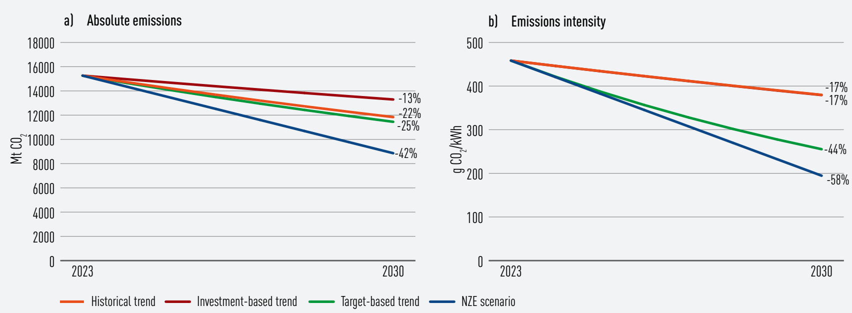
Notes: This figure presents, for the aviation sector, the trajectories of absolute emissions (Scope 1) and sectoral emissions intensity (gCO_2e/pkm) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

Figure 5. Automotive



Notes: This figure presents, for the automotive sector, the trajectories of absolute emissions (Scope 3 downstream) and sectoral emissions intensity (gCO_2e/pkm) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

Figure 6. Electricity



Notes: This figure presents, for the electricity sector, the trajectories of absolute emissions (Scope 1) and sectoral emissions intensity (tCO_2e/kWh) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

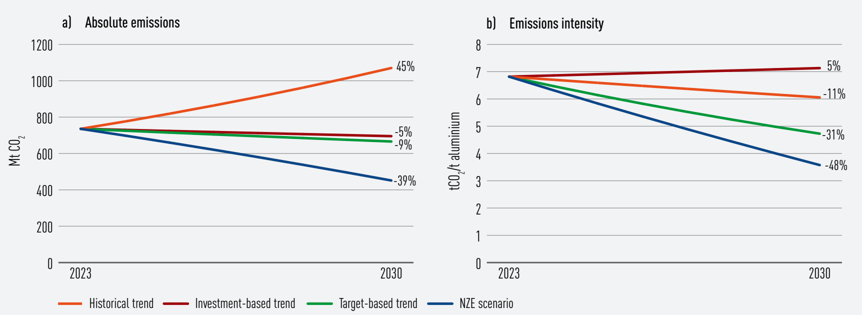
capacity is set to triple by 2030, with wind and solar share of global generation roughly doubling to around 30% by the end of the decade, alongside accelerated coal retirements, greater grid flexibility and rising end-use electrification. These dynamics imply a 58% decline in emissions intensity and a 42% fall in absolute emissions over 2023–30. Relative to this benchmark, corporate targets point to a 44% reduction in intensity, while capex-based and historical trajectories deliver only 17% declines. In absolute terms, target-based and capex-based projections fall by 25% and 13% respectively, and the continuation of recent historical trends by 2%. Overall, while all three perspectives remain above the NZE benchmark, the gap is noticeably narrower in absolute terms for corporate targets and even for recent history, indicating movement in the right direction; nonetheless, a further acceleration is required to bring the power sector fully on to a net-zero-consistent path. However, the power sector exhibits one of the widest intra-sector dispersions across firms, revealing that this aggregate improvement conceals highly uneven transition dynamics among companies.

Somewhere in between: aluminium and cement sectors

In the aluminium sector, the IEA's net-zero pathway envisions rapid efficiency gains stemming from large-scale decarbonisation of electricity inputs, the deployment of inert-anode electrolysis and other process innovations, the electrification and heat-recovery of alumina refining, and an increasing reliance on secondary (scrap-based) production. Consistent with these assumptions, emissions intensity is projected to decline by more than 45% between 2023 and 2030, accompanied by a significant reduction in absolute emissions. Relative to this benchmark, corporate targets indicate a slower yet still substantial decrease in intensity of slightly above 30%, while the continuation of recent historical trends would yield only limited improvements of around 10%, and a capex-based trajectory points to an almost stagnant profile with an increase of 5%. In terms of absolute emissions, the target-based and capex-based pathways are expected to contract by about 10% and 5%, respectively, but both remain above the scenario benchmark by 2030, whereas a continuation of historical dynamics would lead to a sharp expansion of more than 45%.

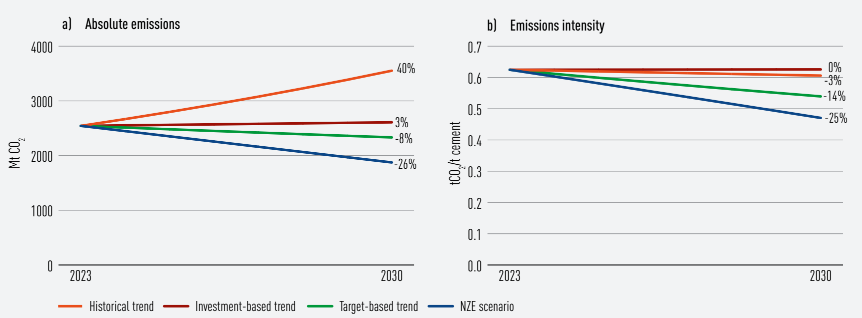
Finally, in the cement sector, the IEA's net-zero emissions pathway relies on a combination of process innovations and demand-side measures, including the substitution of clinker with alternative materials, large-scale deployment of carbon capture and storage, improved kiln efficiency and the shift to low-carbon fuels. These developments are expected to drive a reduction in emissions intensity of about 25% between 2023 and 2030, alongside a decrease in absolute emissions of the same order of magnitude. Relative to this benchmark, corporate targets imply a slower decline of intensity of around 15%, while both capex-based and historical trajectories show little progress, with intensity falling by less than 5%. In terms of absolute emissions, the target-based pathway achieves a reduction of around 10%, but capex-based projections point to constant emissions, and the historical trend suggests a sharp increase. As a result, 2030 emissions remain well above the net-zero benchmark under all three perspectives.

Figure 7. Aluminium



Notes: This figure presents, for the aluminium sector, the trajectories of absolute emissions (Scope 1+2) and sectoral emissions intensity (tCO_2/t aluminium) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. Scope 2 emissions are estimated by combining electricity consumption data for taluminium with a global average grid factor. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is

Figure 8. Cement



Notes: This figure presents, for the cement sector, the trajectories of absolute emissions (Scope 1) and sectoral emissions intensity (tCO_2/t cement) under alternative assumptions. The starting point for both indicators is derived from the IEA World Energy Outlook 2024. The Net Zero Emissions by 2050 (NZE) scenario trajectory is shown in blue. The historical trend implied by the past emissions of the companies in the sample is shown in orange. The trajectory based on companies' stated reduction targets is displayed in green, while the trajectory inferred from firms' investment capacity is represented in red.

Conclusion: implications for investors

Three key results emerged from this analysis. First, while target-based trajectories generally approach scenario-consistent intensity paths (although the absolute trajectories often fall short once production growth is accounted for), capex-based projections tell a very different story: one of an ambition-credibility gap. Second, recent historical trends rarely bridge this gap. Instead, these tend to mirror capex-based paths, reinforcing concerns about feasibility. Third, there are major differences between sectors. Misalignment is most pronounced in steel, oil and gas, shipping and aviation, while electricity and automotive display partial convergence in both intensity and absolute terms (although they also display some of the highest company-level dispersion, reminding us of the importance of a granular approach).

For investors and lenders seeking to understand portfolio emissions and 'alignment', this research illustrates how a strategy focused on targets only is likely to fall short. Instead, stewardship programmes should focus on companies' actions, potentially including capital expenditure data, physical process indicators and absolute emission outcomes.

For regulators, credibility assessment hinges on standardised disclosure of multi-year historical data and harmonised definitions of physical intensity metrics among critical sectors, ensuring consistent treatment of scopes, greenhouse gases and production measures.

The move towards target-setting for decarbonisation, and the participation of institutional investors in encouraging this shift, has been an immensely positive step. Now however, the focus must shift from intention to action, to ensure that these ambitions (and investors' strategies) are not undermined by weak execution.

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GARCH in the machine: using conditional volatility to improve simulated returns

Matteo Bagnara, Senior Quantitative Researcher, Scientific Portfolio;
Benoit Vaucher, Director of Research, Scientific Portfolio

Simulated returns are crucial to investment practitioners: they are the key building block required for back-testing, portfolio construction, risk management (including scenario analysis and regulatory risk assessments) and derivative pricing. Yet equity return simulations are also highly problematic. Academics and other researchers have been deploying econometric and, more recently, machine learning techniques in an effort to overcome these challenges, but the newer approaches also have shortcomings due to onerous computational and data requirements. This article, a summary of an upcoming research paper[1], proposes a novel methodology that combines a successful econometric model with generative neural networks.

Key takeaways

Simulating equity returns is challenging due to several empirical facts that should ideally be reproduced, such as fat tails, serial correlation and volatility clustering.

We propose to combine generative models with an econometric approach. This hybrid methodology produces realistic simulated factor returns that exhibit key features (such as serial dependence, volatility clustering and multivariate correlation structures) that would be nearly impossible to reproduce with a single econometric model. We demonstrate its advantages when applied to disciplines such as extreme risk management and macroeconomic analysis.

Crucially, the calibration also maintains modest resourcing requirements. This sets the model apart from certain innovative methods that produce impressive results but require large datasets and are often affected by computational challenges due to the high noise-to-signal ratio of financial data.

Introduction: return simulation and machine learning

Researchers seeking to generate synthetic (simulated) returns have long struggled with traditional econometric models and their narrow feature range. On the one hand, many commonly used probability distributions capture fatter tails, but are unable to reproduce serial correlations. On the other hand, conditional models such as GARCH (Bollerslev [1986, 1990]) effectively reproduce volatility clustering, but fall short in generating skewness or autocorrelation.

With the advent of machine learning techniques, researchers have naturally turned their attention to these old problems with new tools in hand. Conditional restricted Boltzmann machines (CRBMs – Taylor et al [2006, 2011]) integrate historical data into RBMs, meaning that they can capture both the cross-sectional and temporal correlations in financial time series data. Yet they cannot model serial correlation and volatility clustering simultaneously, due to the lack of a mechanism to explicitly separate the two. Alternative approaches to model all these features at once include Variational Autoencoder models (VAEs – Kingma et al [2013, 2019]) and adversarial networks (Goodfellow et al [2014]). More recently, more intensive deep learning models have been developed using context-dependent features inspired by large language models (eg, Srinivasan and Knottenbelt [2022]). However, these are not easy to calibrate: high sensitivity to hyper-parameters, a propensity for mode collapse and high computational cost have seriously

1 Bagnara, M., and B. Vaucher (2026). C-CRBM: Embedding Time-varying Volatility into Boltzmann Machines for Equity Return Simulations.

hindered their wider adoption, in spite of their impressive outputs.

Despite the evident difficulties, it is now more important than ever for investment practitioners to produce realistic risk factor simulations and to address autocorrelation and volatility clustering. For example, our understanding of serial correlation has evolved considerably in the past five years: autocorrelations in financial returns were historically perceived to be weak, but Lewellen (2022) demonstrated that this may be a misperception arising from reliance on pre-2000 data. We also now know that volatility clustering – when large returns are followed by changes of similar magnitude – may be even more destabilising than heavy tails (Traut and Schadner [2023]). Finally, serial correlations may have a particularly large effect on equity factors during periods of macroeconomic change – typically the very moment when investors are most likely to rely on simulations for making real-world decisions.

Below, we present the key innovation of our approach: instead of relying on either econometrics or neural networks, we use an econometric model – the successful family of GARCH models – to produce volatility clustering, and we use it to enhance a trained NN that has learned the other features of the returns' distribution. GARCH types of models are generally poor at reproducing multivariate returns with tails and some dynamical features such as serial correlations. By combining the econometric and generative approach, the resulting hybrid model – conditional volatility-CRBM or C-CRBM – covers almost all of the statistical features found in financial returns.

The analysis uses weekly returns data from S&P Capital IQ, featuring the 500 largest stocks by market capitalisation, between July 1970 and December 2024. We simulate the returns of seven well-known fundamental risk factors: market, size, value, momentum, volatility, profitability and investment. The market factor is a cap-weighted portfolio including all of the stocks mentioned; the other factors are long-short portfolios obtained using the top and bottom quintile sorted by the corresponding fundamental characteristic.[2] In a second step, we also consider periods of significant macroeconomic shift by using two variables: credit spreads (the difference between yields of BAA versus AAA corporate bonds by Moody's) and long-term rates (10-year Treasury, DSG10).

Methodology: building a C-CRBM

We use a type of neural network known as the Restricted Boltzmann Machine (RBM – Smolensky [1986]; Hinton [2002]). This NN is 'generative' as it learns probability distributions and can generate, for instance, sample of returns.

RBMs are often visually represented by the 'neural network' image on the left-hand side of figure 1. Here, the layer exposed to the training data is called the visible layer and it flows to the hidden layer through the network architecture.

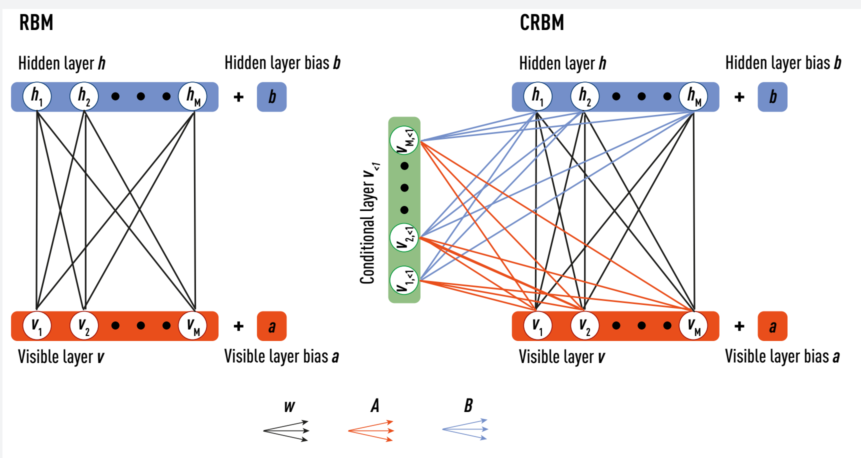
Since these NNs are trained on a large sample of historical returns, they learn the probability distribution of many combinations of returns. Thus, given an input a vector of returns ***v***, they can return its probability of happening. If, historically, value tends to decline when momentum rises, return vectors with opposite signs will receive higher probabilities than those where both factors move in the same direction.

A key feature of our approach is the integration of a 'conditional' layer that incorporates the historical factor performance over the preceding eight weeks, allowing the model to adjust the probability of vector ***v*** based on recent trends. For example, the likelihood of positive returns may differ depending on whether factors have recently experienced sustained declines or strong outperformance.

When we use this conditional probability distribution to generate returns in a GARCH model, it captures far richer dynamics than the conventional Gaussian assumption, which typically reflects only mean and volatility. The NN learns not only risk and return, but also extreme risk and subtle dynamical effects such as evolution in correlations and serial correlations.

What distinguishes a standard CRBM from a C-CRBM is the introduction of GARCH noise into the training and sample procedure. While standard CRBMs are trained and sampled assuming simple Gaussian visible units, we introduce a GARCH-style innovation that follows the conditional volatility generated from this econometric model. In this way, the C-CRBM is encouraged to learn and to generate a dynamic volatility structure instead of a static one, thus delivering the feature of volatility clustering that standard CRBMs cannot generate alone, given the lack of a specific parameter to model dependence among time-varying return volatility.

Figure 1. Simplified illustration of RBM vs CBRM architecture



Source: Scientific Portfolio. The biases *a* and *b* are added to the output of the visible and hidden layer, respectively, to form the input of the activation functions as explained in the text. The matrices *W*, *A*, *B*, which connect the various layers, are represented through arrows.

2 Price-to-book for value, two-year asset growth for profitability, one-year return for momentum, gross profits over total assets for investment, inverse of adjusted market cap for size, volatility of weekly returns over two years for volatility. All factors are market neutral.

Does C-CRBM outperform CRBM in risk factor simulations?

We are going to illustrate now how our combined model performs in different settings compared to a more common GARCH model with static correlations. Importantly, the combination of a generative approach with a GARCH noise injects a considerable amount of volatility clustering (illustrated in figure 2) in the data, thus making the generated time-series more realistic.

Consider the market as an example. Historically, returns display periods of elevated volatility that cluster together, with sharp upward or downward moves compared with calmer periods. At times, positive swings are followed by movements of the same sign, reflecting autocorrelation. The standard CRBM captures overall market risk reasonably well but fails to reproduce clusters of high uncertainty: simulated returns typically fluctuate within the same band. GARCH models, by contrast, successfully capture volatility clustering but struggle to reproduce serial correlations consistently. The C-CRBM combines the strengths of both approaches, producing simulated market returns that more closely resemble historical dynamics.

Figure 2. Example of a risk factor simulation (1 of 250), showing volatility clustering in C-CRBM

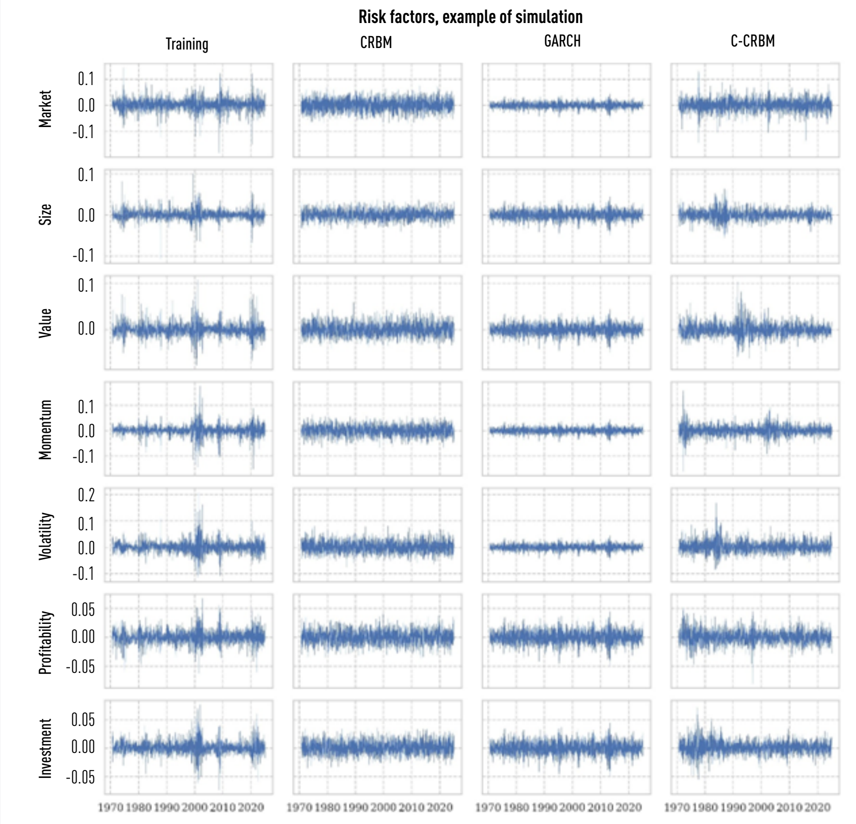


Table 1 shows how the model reproduces the individual features of each factor's returns distribution, while table 2 shows the results for the correlation across factors, which are reproduced with a high degree of precision by CRBM and C-CRBM. A reliable reproduction of correlations is pivotal for multivariate simulations.

The more realistic features of the returns generated with our hybrid approach are confirmed by computing the average Wasserstein distance across each of the 250 simulations for each risk factor, which shows that C-CRBM generates distributions that are closer to the historical data compared to competing methods (unreported results).

Regime-dependent simulations

To further assess the performance of our simulation engine, we consider results for periods when credit spreads (CS) and long-term rates (LT) experience significant changes. Why? Because these two regime types are particularly relevant for portfolio strategists and tend to be characterised by pronounced shifts in the distributional and time-series properties of risk factors. This makes them especially valuable for evaluating our models, which must perform across a wide range of market conditions.

Here, we define a 'credit spread up' (CS UP) or 'long-term rates up' (LT UP) regime as all the days belonging to months during which the monthly change in credit spread or interest rate (respectively) is larger than its historical 75th percentile, accounting for roughly one quarter of the sample in each case. These limited samples would make the calibration of complex NNs difficult. This is why the use of the CRBM shines here: its small size and stable calibration procedure enable its calibration over smaller samples with specific characteristics.

Table 3 compares the historical mean, standard deviation, skewness and first-order autocorrelation and volatility clustering of the risk factors computed over the full sample and during the two regimes considered. Average factor remuneration is, as one might expect, very different during the relevant macro regimes versus the full sample.

We measured the absolute error for each statistic (eg, mean or volatility) between training data and the simulated results for the 250 simulations we performed. Figure 3 reports the average of such error statistics. The lower the error, the higher the quality of the simulations. Compared to the standard CRBM or GARCH, the C-CRBM model leads to more faithful reproduction of the risk factor returns for almost all statistics considered.

To summarise, C-CRBM's ability to match most of the return distribution statistics, including many dynamical effects is confirmed, even when calibrated on limited samples. This makes it an ideal choice for conducting simulations over relatively shorter periods of important macroeconomic shifts.

Estimating extreme risk

Simulations are often used to generate time-varying estimates of risk metrics.

Table 1. Simulations of risk factors – marginal distribution

		Market	Size	Value	Momentum	Volatility	Profitability	Investment
Mean (ann %)	Training	11.4	2.83	0.61	6.21	8.1	2.26	5.81
	CRBM	11.50 (11.50, 11.51)	2.76 (2.76, 2.76)	0.67 (0.67, 0.68)	6.18 (6.18, 6.18)	8.21 (8.20, 8.22)	2.23 (2.23, 2.23)	5.91 (5.91, 5.91)
	GARCH	11.50 (10.14, 12.81)	2.82 (2.35, 3.23)	0.59 (-0.27, 1.44)	6.26 (4.92, 7.73)	8.12 (7.05, 9.14)	2.27 (1.81, 2.76)	5.81 (5.36, 6.28)
	C-CRBM	11.50 (11.48, 11.52)	2.76 (2.76, 2.76)	0.68 (0.66, 0.70)	6.18 (6.17, 6.19)	8.22 (8.19, 8.26)	2.23 (2.23, 2.23)	5.91 (5.91, 5.91)
Standard deviation (ann %)	Training	16.45	8.58	9.82	14.46	15.34	8.19	7.84
	CRBM	16.41 (16.39, 16.43)	8.57 (8.57, 8.58)	9.75 (9.73, 9.78)	14.43 (14.41, 14.44)	15.23 (15.20, 15.26)	8.20 (8.20, 8.20)	7.84 (7.83, 7.85)
	GARCH	16.27 (14.66, 18.36)	8.45 (7.44, 9.68)	9.65 (7.50, 12.83)	14.31 (10.71, 20.17)	15.04 (12.77, 18.47)	8.18 (7.21, 9.47)	7.72 (6.77, 9.25)
	C-CRBM	16.44 (16.36, 16.53)	8.57 (8.57, 8.58)	9.79 (9.73, 9.85)	14.44 (14.38, 14.50)	15.29 (15.17, 15.45)	8.20 (8.20, 8.20)	7.84 (7.82, 7.86)
Skewness	Training	-0.38	0.11	0.59	-0.36	0.68	-0.01	0.2
	CRBM	-0.13 (-0.19, -0.06)	0.03 (-0.05, 0.11)	0.19 (0.12, 0.27)	-0.08 (-0.14, -0.01)	0.18 (0.10, 0.25)	-0.00 (-0.07, 0.07)	0.06 (-0.02, 0.14)
	GARCH	0.01 (-0.24, 0.26)	0.00 (-0.15, 0.16)	-0.01 (-0.19, 0.22)	0.01 (-0.31, 0.37)	-0.00 (-0.18, 0.17)	0.00 (-0.15, 0.15)	0.00 (-0.15, 0.20)
	C-CRBM	-0.27 (-0.56, -0.04)	0.05 (-0.15, 0.23)	0.38 (0.16, 0.60)	-0.21 (-0.54, 0.14)	0.39 (0.10, 0.83)	-0.01 (-0.15, 0.14)	0.13 (-0.11, 0.38)
Kurtosis	Training	5.27	7.72	5.61	9.69	8.56	2.75	5.32
	CRBM	-0.02 (-0.17, 0.16)	-0.04 (-0.16, 0.11)	0.03 (-0.13, 0.24)	-0.03 (-0.15, 0.13)	0.03 (-0.12, 0.17)	-0.04 (-0.17, 0.09)	-0.04 (-0.16, 0.10)
	GARCH	2.88 (0.80, 7.31)	1.33 (0.36, 3.67)	2.30 (0.52, 6.59)	4.89 (0.99, 15.12)	1.76 (0.44, 4.79)	1.15 (0.30, 2.71)	1.56 (0.38, 4.32)
	C-CRBM	2.35 (1.19, 4.32)	1.44 (0.77, 2.50)	2.13 (1.04, 3.68)	3.93 (2.14, 6.51)	2.82 (1.06, 6.76)	0.93 (0.50, 1.52)	1.85 (0.81, 3.60)
1st percentile (%)	Training	-6.23	-2.88	-3.63	-6.25	-5.43	-2.95	-2.8
	CRBM	-5.24 (-5.46, -4.99)	-2.67 (-2.79, -2.56)	-2.93 (-3.03, -2.82)	-4.62 (-4.80, -4.44)	-4.45 (-4.66, -4.28)	-2.59 (-2.71, -2.48)	-2.35 (-2.45, -2.24)
	GARCH	-5.54 (-6.64, -4.74)	-2.88 (-3.47, -2.43)	-3.53 (-5.04, -2.55)	-5.39 (-8.52, -3.62)	-5.17 (-6.88, -4.15)	-2.80 (-3.37, -2.37)	-2.60 (-3.28, -2.14)
	C-CRBM	-5.73 (-6.10, -5.38)	-2.88 (-3.04, -2.71)	-3.18 (-3.36, -3.00)	-5.35 (-5.85, -4.84)	-4.78 (-5.08, -4.50)	-2.75 (-2.91, -2.60)	-2.52 (-2.70, -2.37)
99th percentile (%)	Training	5.92	3.52	4.07	5.39	5.96	2.97	3.14
	CRBM	5.25 (5.08, 5.45)	2.83 (2.71, 2.95)	3.33 (3.18, 3.48)	4.64 (4.48, 4.82)	5.33 (5.10, 5.55)	2.66 (2.57, 2.76)	2.67 (2.55, 2.78)
	GARCH	6.01 (5.17, 7.11)	2.98 (2.51, 3.50)	3.53 (2.54, 5.07)	5.63 (3.81, 8.46)	5.50 (4.46, 7.31)	2.89 (2.45, 3.46)	2.83 (2.37, 3.57)
	C-CRBM	5.64 (5.34, 5.95)	3.03 (2.85, 3.21)	3.71 (3.46, 3.98)	5.28 (4.90, 5.74)	5.79 (5.41, 6.26)	2.83 (2.68, 3.01)	2.90 (2.71, 3.09)
Autocorrelation (1)	Training	-0.06	0.11	0.11	0.01	0.01	0.05	0.03
	CRBM	-0.05 (-0.09, -0.02)	0.13 (0.10, 0.16)	0.13 (0.09, 0.16)	0.03 (-0.00, 0.06)	0.04 (0.01, 0.07)	0.07 (0.04, 0.11)	0.04 (0.01, 0.07)
	GARCH	-0.00 (-0.05, 0.05)	0.00 (-0.04, 0.04)	0.00 (-0.04, 0.05)	0.00 (-0.05, 0.06)	-0.00 (-0.04, 0.04)	0.00 (-0.04, 0.04)	0.00 (-0.05, 0.04)
	C-CRBM	-0.07 (-0.11, -0.03)	0.12 (0.08, 0.15)	0.11 (0.07, 0.15)	0.01 (-0.04, 0.06)	0.03 (-0.01, 0.06)	0.05 (0.02, 0.09)	0.03 (-0.01, 0.07)
Volatility clustering	Training	0.26	0.24	0.18	0.29	0.27	0.19	0.26
	CRBM	0.00 (-0.03, 0.03)	0.02 (-0.01, 0.05)	0.01 (-0.02, 0.04)	-0.00 (-0.03, 0.03)	0.00 (-0.03, 0.03)	0.00 (-0.03, 0.04)	0.00 (-0.03, 0.03)
	GARCH	0.27 (0.19, 0.37)	0.17 (0.10, 0.26)	0.22 (0.12, 0.37)	0.31 (0.19, 0.46)	0.20 (0.11, 0.32)	0.16 (0.09, 0.26)	0.17 (0.10, 0.28)
	C-CRBM	0.13 (0.09, 0.18)	0.12 (0.08, 0.17)	0.14 (0.09, 0.18)	0.21 (0.16, 0.27)	0.13 (0.08, 0.19)	0.09 (0.05, 0.12)	0.12 (0.07, 0.18)

Source: Scientific Portfolio. The table reports mean, standard deviation, skewness, kurtosis, first and 99th percentile, first-order autocorrelation as well as volatility clustering obtained as first-order autocorrelation of absolute returns, for the training data and the average of 250 simulations obtained with the CRBM, GARCH and C-CRBM. Simulation 95% confidence intervals are in brackets.

For example, by simulating a large number of alternative return paths, we can compute a dynamic VaR_α measure by extracting the α-percentile across the simulations at each point in time. Given its conditional nature, the C-CRBM offers the possibility of estimating extreme risk, taking into account the recent trajectory. We performed a selection of classic VaR backtests in order to understand how C-CRBM performed in this respect: Basel traffic light test, Kupiec (1995) proportion of failures test and Christoffersen (1998) independence test. These showed that embedding conditional volatility into the CRBM structure produces better simulations, which in turn yield more reliable extreme losses estimates for regulatory and risk management contexts.

How sensitive are CRBMs to starting point?

As conditional models, CRBMs rely on past input information and therefore depend on the chosen starting date. For medium- to long-term return simulations, it is important to assess how the starting point influences the generated series and how quickly their distributional properties converge to long-term behaviour. Figure 4 illustrates the results of this analysis for three of the seven factors. We use the expanded mean return to measure how the starting point impacts the rest of the trajectory. This is a very sticky statistic, in the sense that an event will remain visible until it no longer affects the long-term average. The 20 starting dates were chosen to represent a mix of different market regimes, including days belonging to seven NBER recession periods (red lines), as well as 13 other random dates (green lines). In general, the impact of the initial event remains statistically present for about a year. For the most impactful starting date (2020, COVID-19 recession; dark red dotted line), we find that trajectories for size and value factor converge to the empirical mean after about 150 steps, while the convergence

Table 2. Simulations of risk factors – factor correlation

		Training	CRBM	GARCH	C-CRBM
Market	Size	0.16	0.17 (0.14, 0.19)	0.15 (0.12, 0.18)	0.15 (0.12, 0.17)
	Value	-0.02	-0.02 (-0.05, 0.01)	-0.02 (-0.06, 0.01)	-0.02 (-0.04, 0.01)
	Momentum	0.01	0.00 (-0.03, 0.04)	0.01 (-0.02, 0.04)	0.01 (-0.03, 0.04)
	Volatility	-0.02	-0.02 (-0.05, 0.01)	-0.02 (-0.04, 0.01)	-0.02 (-0.05, 0.01)
	Profitability	-0.01	-0.01 (-0.04, 0.02)	-0.01 (-0.04, 0.02)	-0.01 (-0.04, 0.02)
	Investment	-0.02	-0.02 (-0.05, 0.01)	-0.02 (-0.05, 0.01)	-0.02 (-0.06, 0.00)
Size	Value	0.49	0.49 (0.47, 0.52)	0.45 (0.40, 0.48)	0.44 (0.42, 0.47)
	Momentum	-0.47	-0.47 (-0.50, -0.45)	-0.42 (-0.46, -0.36)	-0.42 (-0.45, -0.39)
	Volatility	-0.31	-0.32 (-0.35, -0.29)	-0.29 (-0.32, -0.26)	-0.29 (-0.32, -0.27)
	Profitability	-0.17	-0.17 (-0.20, -0.13)	-0.16 (-0.19, -0.13)	-0.16 (-0.19, -0.13)
	Investment	-0.03	-0.03 (-0.06, -0.00)	-0.03 (-0.06, 0.01)	-0.03 (-0.07, -0.00)
Value	Momentum	-0.55	-0.54 (-0.57, -0.52)	-0.48 (-0.53, -0.42)	-0.48 (-0.51, -0.44)
	Volatility	0.01	0.01 (-0.02, 0.05)	0.01 (-0.02, 0.04)	0.01 (-0.02, 0.04)
	Profitability	-0.55	-0.56 (-0.58, -0.53)	-0.51 (-0.54, -0.47)	-0.50 (-0.53, -0.47)
	Investment	0.35	0.35 (0.32, 0.38)	0.31 (0.28, 0.35)	0.31 (0.28, 0.34)
Momentum	Volatility	0.14	0.14 (0.12, 0.17)	0.12 (0.09, 0.15)	0.13 (0.10, 0.16)
	Profitability	0.13	0.13 (0.09, 0.16)	0.11 (0.08, 0.14)	0.12 (0.09, 0.15)
	Investment	-0.01	-0.01 (-0.04, 0.02)	-0.01 (-0.04, 0.02)	-0.00 (-0.03, 0.03)
Volatility	Profitability	-0.05	-0.05 (-0.09, -0.02)	-0.05 (-0.08, -0.02)	-0.05 (-0.08, -0.02)
	Investment	0.46	0.46 (0.44, 0.48)	0.43 (0.39, 0.46)	0.42 (0.39, 0.45)
Profitability	Investment	-0.16	-0.16 (-0.20, -0.13)	-0.15 (-0.18, -0.12)	-0.15 (-0.18, -0.12)

Source: Scientific Portfolio. The table reports factor Pearson correlations for the training data and the average of 250 simulations obtained with the CRBM, GARCH and C-CRBM. Simulation 95% confidence intervals are in brackets.

Table 3. Risk factor statistics – full sample vs regimes

	Mean (ann, %)			Standard deviation (ann, %)			Autocorrelation			Volatility clustering		
	Full sample	CS UP	LT UP	Full sample	CS UP	LT UP	Full sample	CS UP	LT UP	Full sample	CS UP	LT UP
Market	11.40	8.69	4.47	16.45	19.85	-0.29	-0.06	-0.06	0.00	0.26	0.22	0.18
Size	2.83	3.41	4.92	8.58	9.25	0.17	0.12	0.10	0.13	0.24	0.19	0.17
Value	0.61	-2.88	8.38	9.82	10.55	0.84	0.11	0.14	0.00	0.19	0.15	0.18
Momentum	6.21	8.53	2.92	14.46	16.09	-0.20	0.01	0.05	0.07	0.29	0.25	0.22
Volatility	8.10	15.97	-10.90	15.34	18.05	0.45	0.01	-0.02	0.02	0.27	0.28	0.15
Profitability	2.26	4.03	1.89	8.19	9.26	-0.50	0.05	0.04	0.03	0.19	0.23	0.22
Investment	5.81	5.03	7.70	7.84	8.67	0.20	0.03	0.06	-0.01	0.26	0.20	0.25

The table reports historical annualised mean returns (%), annualised standard deviation (%), skewness and first-order autocorrelation and volatility clustering (with absolute returns) for the risk factors reported on the rows over the full sample, the high credit spread regime (CS UP) and the high long-term rates regime (LT UP).

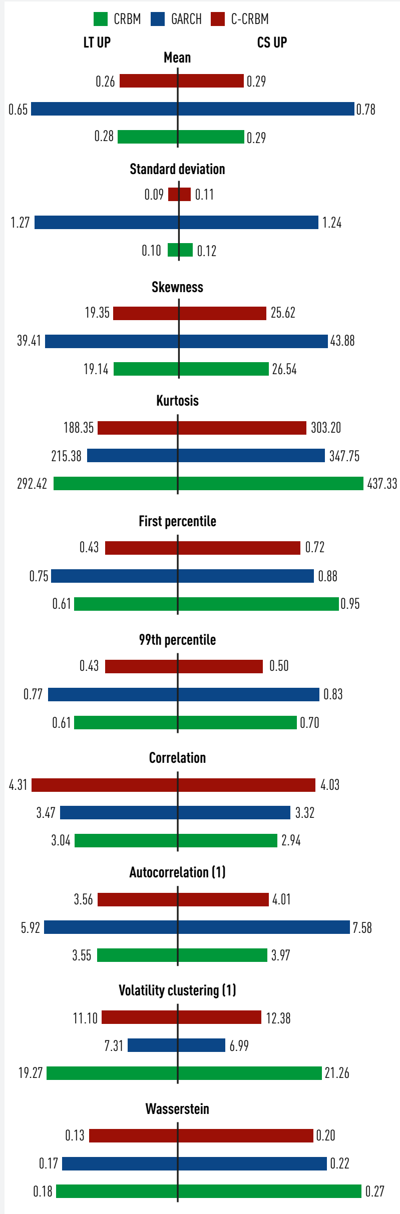
for the market occurs earlier, around 100 steps even from the date where the mean starts the farthest away from the long-run one (1980). With weekly data, this corresponds to a two- to three-year period before the influence of the starting point dissipates.

The sensitivity to the starting point is an important feature for the distribution of many financial assets. Yet most simulation models are blind to history to generate returns. The conditionality embedded in the CRBM fills this gap as it learns the dependency of the next returns on their recent history.

Conclusion

This article tackles a central challenge in financial data simulation: reproducing key stylised facts – such as serial dependence and volatility clustering – within a model that is both computationally tractable and multivariate. We propose a hybrid C-CRBM framework that combines the econometric strengths of GARCH with the flexibility of a non-parametric generative

Figure 3. Average error (10^2) to training – regime simulations



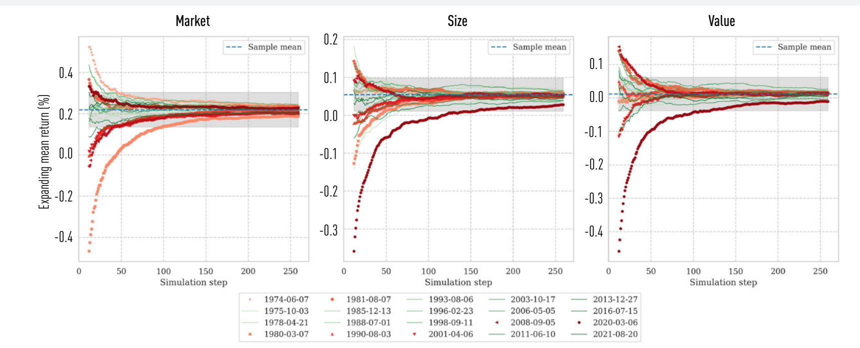
Source: Scientific Portfolio. This figure represents the absolute error between the training returns and simulated returns with the standard CRBM, the GARCH model and the C-CRBM model, averaged over 250 simulations, multiplied by 100 to improve readability.

Table 4. Simulations, risk measures backtest

		VaR 95%				VaR 99%			
		Norm	**CRBM**	**C-CRBM**	**GARCH**	**Norm**	**CRBM**	**C-CRBM**	**GARCH**
Basel traffic light test	Market	Red	Green	Green	Green	Red	Red	Yellow	Red
	Size	Red	Green	Green	Green	Red	Yellow	Yellow	Yellow
	Value	Red	Green	Green	Green	Red	Red	Yellow	Green
	Momentum	Red	Green	Green	Yellow	Red	Red	Yellow	Yellow
	Volatility	Red	Green	Green	Green	Red	Red	Yellow	Yellow
	Profitability	Red	Green	Green	Green	Red	Red	Yellow	Yellow
	Investment	Red	Green	Green	Green	Red	Yellow	Yellow	Yellow
Kupiec POF	Market	0	**0.263**	**0.555**	**0.228**	0	0	0.006	0
	Size	0	0.004	**0.081**	**0.166**	0	0.004	0.006	0.01
	Value	0	0.013	**0.117**	0.035	0	0	0.001	**0.227**
	Momentum	0	**0.066**	**0.945**	**0.051**	0	0	0.01	0.006
	Volatility	0	**0.393**	**0.85**	**0.656**	0	0	0.004	0.039
	Profitability	0	**0.498**	**0.742**	**0.393**	0	0	0.004	0.016
	Investment	0	0	0.004	0.004	0	0.01	**0.084**	**0.119**
Christoffersen independence	Market	0.002	0	0	0	0.003	0	0	0
	Size	0	0	0	0	0	0.006	**0.715**	0
	Value	0	0.004	0.015	0.016	0	0.001	**0.062**	0.001
	Momentum	0	0.001	0	0	0	0.006	**0.179**	**0.186**
	Volatility	0	0	0	0	0	0	0	0
	Profitability	0	0	0.001	0	0	**0.105**	**0.776**	**0.171**
	Investment	0	0	0.002	0	0	0.001	0.018	**0.106**

The table reports statistics for backtests of VaR at the factor-risk level according to a Gaussian simulation obtained using one-year rolling mean and standard deviations of the risk factors (Norm), and the simulations obtained with CRBM, C-CRBM and GARCH. The three panels present p-values for three VaR backtests: the Basel traffic light test (BTL), the Kupiec (1995) proportion of failures test and the Christoffersen (1998) independence test. p-values in bold denote cases where the test is passed. The results are displayed for 95% VaR (left) and 99% VaR (right).

Figure 4. Sensitivity to starting point



This figure plots weekly expanding mean returns (in %) for market, size and value factor returns, for the C-CRBM model. Expanding means are cumulative mean returns computed starting with 13 simulations steps up until 260 steps. Each line corresponds to the average across 250 simulations, each of which starts at the date indicated in the legend. Red lines refer to NBER recession dates as starting points. The dashed line is the full-sample empirical factor mean return, with shaded areas representing its 95% confidence intervals.

neural network. The resulting model generates highly realistic return series while incorporating recent market history. Unlike many deep generative approaches – that often come with heavy computational demands – our framework captures complex dynamics in a multivariate setting with comparatively modest resources.

Empirically, the C-CRBM model produces synthetic returns whose higher-order moments and autocorrelation structures closely match recent historical data. Improvements are reflected in the accurate reproduction of correlations, autocorrelations and volatility clustering – core features of financial returns. The model also preserves risk-factor behaviour during periods of macroeconomic stress and proves suitable for regulatory risk assessment: value-at-risk estimates derived from the simulations pass regulatory backtests more consistently than those from simpler models.

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Quantifying climate physical loss and heterogeneity Part 1: European equities

Vincent Bouchet, Director of ESG and Climate Research, Scientific Portfolio; **Nicolas Schneider**, Senior Research Engineer – Macroeconomist, EDHEC Climate Institute

How can we quantify the potential equity portfolio losses that may be attributed to physical climate risk in the future? Over recent years, it has become increasingly important for pension funds and other investors to answer this question in ways that are credible, transparent and in tune with regulators' requirements. In this article (a summary of a recent paper[1]), we examine the European equity market using a climate physical loss (CPL) framework. The methodology is top-down, parsimonious, based on public data, and aligned with the NGFS scenario set.[2] Importantly, it is also directly applicable to asset allocation and portfolio construction due to its use of a discounted cash-flow model and, therefore, of practical use to investors seeking not simply an assessment framework but a useable portfolio management tool.

This article explicitly focuses on European equities, while the following article (Part 2: US equities) presents an application to US listed equities.

Key takeaways

We find that European countries on average exhibit lower macroeconomic sensitivity to physical climate risks than the US, although there is a substantial amount of sector- and country-level heterogeneity, with larger projected deviations of nominal GDP in southern regions (eg, -28% in Spain by 2100 under the NGFS 'current policy' scenario versus modest gains in Finland).

However, we find that the European cap-weighted equity benchmark displays a larger CPL of -4.7%, versus -4.0% for the US benchmark.

This apparent dampening effect is primarily driven by benchmark composition, with the European equity market more exposed to low-WACC, higher-sensitivity sectors and more concentrated in physically vulnerable regions than its US counterpart. As such, the research highlights the importance of portfolio construction in determining resilience.

Introduction: physical climate risk

Physical acute climate hazards such as heatwaves, floods, droughts, storms and/or chronic sea-level rise increasingly represent a challenge for firms and governments, as well as financially material risks for investors. Regulatory and supervisory authorities increasingly acknowledge that physical climate risks must be systematically integrated into risk management frameworks. The recommendations of the Task Force on Climate-related Financial Disclosures (TCFD), followed by the issuance of the International Sustainability Standards Board's IFRS S2 standard, have formalised the requirement to identify and disclose material physical and transition risks, underpinned by robust scenario analysis.

In Europe, regulatory and supervisory authorities have strongly acknowledged that climate-related risks may already be financially material and warrant forward-looking assessment. The European Central Bank's 2022 climate stress test incorporated physical climate risk scenarios and demonstrated that these risks can materially affect banks' risk profiles. Similarly, the European Securities and Markets Authority (ESMA) has documented substantial exposure of EU investment funds to physical climate hazards.

In parallel with regulatory developments, an extensive academic literature has emerged to demonstrate how climate-related risks are reflected in asset prices and establish forward-looking methodologies such as short-term stress tests and long-term scenario analyses

1 Bouchet, V., and N. Schneider (2026a). Physical Climate Risk in the European Equity Market: Quantifying Country-Sector Heterogeneity.

2 NGFS Scenarios Portal, Network for Greening the Financial System.

Climate physical loss:

the reduction in valuation arising from climate-induced physical damage.

(which typically rely on integrated assessment models to quantify climate-related value-at-risk or evaluate changes in discounted cash flows under alternative temperature or policy pathways). However, these analyses are generally conducted at high levels of geographic and macroeconomic aggregation. While these are well suited for wide systemic risk assessments, investors lack further information granularity for strategic investment management.

As such, this article presents a methodology that is directly applicable to institutional investors and asset managers who are looking to understand CPL for their own equity portfolios. This approach has the advantage of providing answers through a transparent and intuitive framework, without imposing onerous or resource-intensive data requirements.

Building and calibrating a climate physical loss framework

The proposed CPL framework rests on the principle that physical climate risk affects firm value through its impact on macro-economic activity and, ultimately, on expected future cash flows. As such, a firm-level CPL is the difference between a firm's baseline enterprise value and an alternative valuation in which future cash flows are scaled by macroeconomic losses attributable to physical climate risks.

Formally, the procedure consists of three steps: (i) quantifying country-level projected GDP losses as a function of temperature anomalies; (ii) transmitting these losses to firm valuations through a discounted cash-flow framework; and (iii) reweighting relative valuation losses using sector-level sensitivity scores.

Step 1: estimating regional GDP losses as a function of temperature anomalies
Country-level macroeconomic projections are sourced to obtain both the baseline trajectory of aggregate economic activity and the relative deviations from this trajectory induced by global temperature anomalies. Country-level deviations are sourced from NGFS scenario outputs.[3]

The global non-linear effect of temperature on economic production has been empirically confirmed by Burke et al (2015) and Newell et al (2021), providing evidence for an inverted U-shaped relationship whereby average temperatures exceeding a turning point generate amplifying reductions in per capita GDP. To begin, we first estimate an aggregate damage function at the country-level, linking physical risk-induced country-level GDP damages (arising from both chronic and acute climate risk) to a non-linear function of global temperature anomalies, as emulated by NGFS MAGICC across scenarios and IAMs,

$$\Delta y_{i,t} = \beta^{G}_{1,i} \Delta T_t + \beta^{G}_{2,i} \left(\Delta T_t \right)^2 + \varepsilon_{i,t}$$

where global temperature anomaly ΔT_t is measured relative to a reference year t_0 and where $\Delta y_{i,t}$ denotes the percentage deviation of real GDP from a no-damage baseline.

From the estimated aggregate damage function, nominal GDP growth factors under the baseline and physical-risk scenarios are defined as

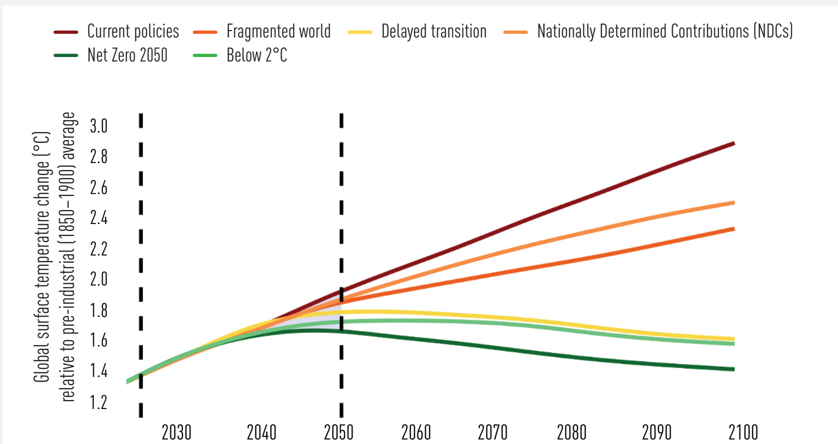
$$G^{base}_{s,t} = \frac{Y^{real,base}_{i,t}}{Y^{real,base}_{i,t0}} P_t, \quad G^{phys}_{s,t} = \frac{Y^{real,base}_{i,t}}{Y^{real,base}_{i,t0}} \left(1 + \Delta y_{s,t}\right) P_t,$$

where P_t denotes the aggregate price level. These factors scale firm-level cash flows in the valuation stage.

Step 2: Transmitting these losses to company valuations through a DCF model
The next stage is to incorporate those deviations into a discounted cash-flow (DCF) model: firm-level cash flows are assumed to grow with country nominal GDP and are discounted using sector-specific weighted average costs of capital (WACC).

The discount rates used in the discounted cash-flow model are obtained from Damodaran's publicly available

Figure 1. Global mean temperature scenario trajectories



Data from NGFS, IPCC. Interpolation under GCAM 6.0 NGFS IAM. Global surface temperature (GSAT) projection from the MAGICCv7.5.3 climate model, based on AR6 climate diagnostics used by NGFS Phase-V.

3 The European economic sensitivity to a non-linear function of global temperature anomalies, $\beta^{G}_{1,i}$ and $\beta^{G}_{2,i}$ is estimated using the NGFS Phase 5 scenario dataset. This provides combinations of qualitative transition narratives and quantitative outputs from integrated assessment models (IAMs) that generate transition and physical risk dynamics (eg, REMIND, MESSAGE). For each scenario–model configuration, the NGFS reports projected country-level paths of real GDP. Rather than using these GDP projections directly, the dataset is used to re-quantify the relationship between global temperature anomalies and deviations of country-level GDP from baseline. Long-horizon nominal GDP projections are derived from two components: (i) a baseline scenario that represents the path of economic activity in the absence of climate damages through 2100, and (ii) a physical-risk scenario in which global temperature anomalies are mapped into country-level economic losses. For long-term projections (post-2050), the baseline real-activity path combines projections from the NGFS and the IPCC–SSP2 framework. Country-level deviations are generated by applying the estimated damage coefficients to an exogenous global mean temperature (GMT) trajectory. The sequence of global temperature anomalies is inserted into the quadratic damage function above to obtain non-linear and country-specific GDP deviations $\Delta^{y}_{i,t}$. When combined with the baseline GDP trajectory, these deviations yield the physical-risk and baseline GDP growth factors, $G^{phys}_{i,t}$ and $G^{base}_{i,t}$, which in turn determine the evolution of firms' expected cash flows. For more information, see Bouchet and Schneider (2026a). Physical Climate Risk in the European Equity Market: Quantifying Country-Sector Heterogeneity.

estimates, which provide sector-level values for different regions.[4]

From a model construction perspective, we can let firms be indexed by j, and denote by $s(j)$ the country of firm j and by $k(j)$ its sector. Cash flows in the reference year t_0 are given by CF_{j,t_0}. For horizon $t_0 + 1$ to T, the baseline enterprise value follows[5]

$$EV_j^{base} = \sum_{t=t_0+1}^{T} \frac{CF_{j,t_0} \times G_{s(j),t}^{base}}{\left(1+r_{k(j)}\right)^{t-t_0}},$$

where $r_{k(j),i(j)}$ is the sector- and region-specific discount rate (weighted average cost of capital). Under the physical-risk scenario:

$$EV_j^{phys} = \sum_{t=t_0+1}^{T} \frac{CF_{j,t_0} \times G_{s(j),t}^{phys}}{\left(1+r_{k(j)}\right)^{t-t_0}},$$

Since CF_{j,t_0} is common to both valuations, the relative enterprise value loss simplifies to our primary impact metric,

$$EV_j^{rel} = \frac{\sum_{t=t_0+1}^{T} \frac{G_{s(j),t}^{phys}}{\left(1+r_{k(j)}\right)^{t-t_0}}}{\sum_{t=t_0+1}^{T} \frac{G_{s(j),t}^{base}}{\left(1+r_{k(j)}\right)^{t-t_0}}} - 1.$$

Thus, EV_j^{rel} measures the proportional decline in firm value solely attributable to physical climate damages.

Step 3: Reweighting relative valuation losses using sector-level sensitivity scores
In the third stage, a final adjustment is applied to reflect the prevailing market assessment of the sensitivity of different sectors to physical climate risk. Various ESG data providers report scores measuring sectors' perceived vulnerability to physical climate risk. Our model incorporates empirical evidence from Hain, Kölbel and Leippold (2022), who compare six firm-level physical risk scores from commercial and academic sources. Although the providers differ markedly in methodology, the authors document substantial systematic variation across sectors: utilities, energy and materials consistently appear as the most exposed sectors, while healthcare, communication services and information technology exhibit comparatively low exposure. This data is used to produce a sector-adjusted relative enterprise value loss such that losses are scaled upward in highly exposed sectors and downward in less exposed sectors.[6]

Figure 2. Sector-specific characteristics

Sector (TRBC)	S1	S2	S3	S4	S5	S6	avg_rank_k	$adj_k(\alpha = 0.2)$	$adj_k(\alpha = 0.5)$	r_k
Utilities	1	1	4	11	1	1	**3.2**	1.20	1.50	5.6%
Energy	4	2	1	7	5	4	**3.8**	1.16	1.39	6.4%
Basic materials	5	3	2	8	2	2	**3.8**	1.16	1.39	7.8%
Industrials	6	4	4	3	2	7	**4.8**	1.08	1.21	7.2%
Non-cyclical consumer*	7	5	5	4	8	3	**5.3**	1.05	1.12	5.9%
Cyclical consumer**	3	8	9	6	6	6	**6.3**	0.97	0.94	7.5%
Financials	11	9	3	1	7	8	**6.5**	0.96	0.90	5.8%
Technology	10	7	6	5	10	9	**7.8**	0.87	0.66	8.9%
Healthcare	9	6	7	10	9	11	**8.7**	0.80	0.50	8.8%
Telecoms	8	10	10	3	11	10	**8.7**	0.80	0.50	6.1%
*(Real estate***)*	*2*	*11*	*11*	*9*	*4*	*5*	*7.0*	-	-	

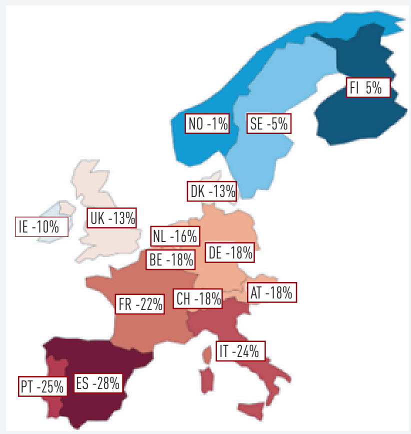
The first seven columns of this table are from Hain, Kölbel and Leippold (2022). They show sector rankings of six different ESG data providers based on the sensitivity of sectors to climate physical risks: Trucost (S1), Carbon4 Finance (S2), Southpole (S3), Truvalue Labs (S4), Sautner et al (S5) and Kölbel et al (S6).
* Consumer staples in Kölbel et al (2024), ** Consumer discretionary, *** Communication services, *** Original sector from Kölbel et al (2024), not covered in TRBC (included in financials).

Results: how exposed is the European market to physical climate risks?

Using the above model, we conducted empirical analysis focused on the 423 largest publicly listed European firms. This allowed us to assess:
- the climate physical risk sensitivity of different European countries;
- how sector-specific discount rates and sector-level exposure to physical hazards affect outcomes; and
- implications for European equity portfolio valuation.

Among the 15 countries considered, projected long-term economic outcomes exhibit substantial heterogeneity. Three clusters emerge in broad agreement with the literature on this topic (Burke et al [2015]; Kalkuhl and Wenz [2020]; Linsenmeier [2023]; Kotz et al [2024]; Schneider [2025]; Bilal and Känzig [2026]). Northern European countries face the mildest impacts, with projected economic trajectories ranging from a gain of approximately 5% for Finland to a loss of 16% for the Netherlands. A second group, including Belgium, Germany, Switzerland and Austria, exhibits relatively homogeneous losses between 18% and 19%. By contrast, the southern economies incur substantially larger declines, with France, Italy, Spain and Portugal all exceeding a 20% relative GDP loss by 2100 (figure 3).

Figure 3. Projected nominal GDP loss in Europe by 2100 under current policies



The figure reports, for each country of our sample, the projected relative loss in nominal GDP in 2100 under the NGFS current policies scenario (GCAM model), expressed as a percentage deviation from the corresponding baseline trajectory.

4 Firm-specific discount rates are computed by assigning each TRBC sector to the appropriate set of Damodaran industry classifications. Information on the sector and country classification of stocks is sourced from CIQ, while the portfolio weights of stocks are taken from the Scientific Portfolio Capital Weight Regional Benchmark for Developed Europe.
5 T is assumed to be far enough in the future to make any terminal value relatively negligible after discounting.
6 Again, for more details on the integration of these sensitivity scores into the enterprise value loss calculation, see Bouchet and Schneider (2026a). Physical Climate Risk in the European Equity Market: Quantifying Country-Sector Heterogeneity.

A second determinant of climate-related economic damage is the underlying GDP growth trajectory. Holding other factors constant, economies with faster baseline growth experience larger current physical loss estimates, as higher future output amplifies the discounted impact of climate-induced deviations. Italy and Spain, which already feature among the most adversely affected countries in terms of 2100 GDP losses, also record the strongest baseline growth rates. This combination results in an increased present value of their projected CPLs. This is discussed further in Bouchet and Schneider (2026a).

Next, we look at sector-level heterogeneity. Sectors such as utilities or non-cyclical consumer – which typically exhibit relatively low WACC – are valued on the basis of long-term cash flows and are therefore more exposed when the distant flows are impacted by physical risks. Conversely, high-WACC sectors such as technology are priced primarily on near-term cash flows, which makes their valuations less sensitive to physical risk shocks affecting distant flows. Incorporating this sectoral adjustment generates substantial dispersion in climate-induced valuation effects, with a ratio of approximately 1.6 between the most and least sensitive sectors (figure 4).

A second sectoral adjustment concerns the sectors' perceived vulnerability to physical climate risks: certain sectors are more vulnerable to physical risks (eg, utilities, energy and materials).[7] Because the initial degree of vulnerability is specified in terms of a ranking, its conversion into a valuation relies on an additional parameter α that can take different values to modulate the influence on the final CPL. As α is difficult to estimate empirically, the analysis evaluates the sensitivity of results to alternative values, focusing on $\alpha = 0.2$ and $\alpha = 0.5$ as plausible bounds. Results show that varying α not only alters the magnitude of CPL within a given country but may also change the ordering of the most affected sectors. This arises from the interaction with the discount-rate effect. For some sectors, such as utilities, a relatively low discount rate is compounded by high vulnerability (ie, a high adjustment factor) identified in the literature, whereas for other sectors, such as financials, the effect of a low discount rate is dampened by their relatively low perceived vulnerability to physical risks.[8]

Figure 4. Effect of sector-specific discount rate only on climate physical loss

Country	Utilities	Financials	Non-cyclical consumer	Telecoms	Energy	Industrials	Cyclical consumer	Basic materials	Healthcare	Technology
ES	-11.0%	-10.7%	-10.4%	-10.2%	-9.7%	-8.6%	-8.4%	-8.0%	-6.9%	-6.8%
PT	-9.3%	-9.0%	-8.8%	-8.6%	-8.2%	-7.3%	-7.1%	-6.8%	-5.8%	-5.8%
IT	-8.2%	-8.0%	-7.8%	-7.6%	-7.3%	-6.5%	-6.3%	-6.0%	-5.2%	-5.1%
FR	-7.8%	-7.6%	-7.4%	-7.3%	-6.9%	-6.1%	-5.9%	-5.7%	-4.9%	-4.8%
AT	-6.1%	-5.9%	-5.7%	-5.6%	-5.4%	-4.7%	-4.6%	-4.4%	-3.8%	-3.7%
BE	-6.0%	-5.8%	-5.7%	-5.6%	-5.3%	-4.7%	-4.5%	-4.3%	-3.7%	-3.7%
CH	-5.8%	-5.7%	-5.5%	-5.4%	-5.1%	-4.5%	-4.4%	-4.2%	-3.6%	-3.6%
DE	-5.8%	-5.7%	-5.5%	-5.4%	-5.1%	-4.5%	-4.4%	-4.2%	-3.6%	-3.5%
NL	-5.5%	-5.3%	-5.2%	-5.1%	-4.8%	-4.3%	-4.2%	-4.0%	-3.4%	-3.4%
UK	-4.8%	-4.7%	-4.6%	-4.5%	-4.3%	-3.8%	-3.6%	-3.5%	-3.0%	-2.9%
DK	-4.2%	-4.1%	-4.0%	-3.9%	-3.7%	-3.3%	-3.2%	-3.1%	-2.6%	-2.6%
IE	-3.8%	-3.7%	-3.6%	-3.6%	-3.4%	-3.0%	-2.9%	-2.8%	-2.4%	-2.4%
SE	-1.7%	-1.6%	-1.6%	-1.6%	-1.5%	-1.3%	-1.3%	-1.2%	-1.0%	-1.0%
NO	-0.3%	-0.3%	-0.3%	-0.3%	-0.2%	-0.2%	-0.2%	-0.2%	-0.2%	-0.1%
FI	1.8%	1.7%	1.7%	1.6%	1.5%	1.4%	1.3%	1.3%	1.1%	1.1%

This heatmap displays the CPL for each country–sector pair after incorporating sector-specific discount rates. Sectors with low WACC tend to exhibit higher CPL as they are more sensitive to the long-term impact of climate change on their cash flows. Results are based on the NGFS Current Policies scenario, using the GCAM model at the 2100 horizon.

Application to a diversified Developed Europe equity benchmark

Within the sample of European countries and sectors, the estimated CPL spans a wide range, from −16.5% to +2.6% after adjustment to take into account the sectors' perceived vulnerability to physical climate risks. Portfolio-level exposure is therefore highly sensitive to the underlying region and sector allocation. For the diversified Developed Europe equity benchmark, the portfolio-weighted CPL amounts to −4.7%. Figure 5 illustrates how alternative country and sector weightings would influence this result. Under an equal-weight allocation across all countries (15) and sectors (10) of our sample, the CPL would be −4.46%. Replacing equal sector weights with the benchmark's sector weights slightly improves the CPL to −4.18%, implying a favourable sector-allocation effect. In contrast, applying the benchmark's country weights while maintaining equal sector weights yields a CPL of −4.93%, corresponding to an adverse country-allocation effect. This decomposition suggests that the benchmark's sector allocation slightly mitigates physical risk exposure, but that this relative gain from the sector effect is more than offset by a negative country-allocation effect. This can be traced back to the overweight positions in countries with higher physical risk exposure.

Figure 5. Climate physical loss of a diversified Developed Europe equity benchmark

Allocation	Country allocation	Sector allocation	Weighted CPL
Equal country and equal sector (baseline)	Equal	Equal	−4.46%
Equal country and portfolio sector	Equal	Portfolio	−4.18%
Portfolio country and equal sector	Portfolio	Equal	−4.93%
Developed Europe equity benchmark	**Portfolio**	**Portfolio**	**−4.67%**

The table reports the weighted climate physical loss (CPL) under alternative allocations. 'Equal' allocates identical weights to each of the 15 countries (or 10 sectors) in the sample, while 'Portfolio' applies the weights of the Developed Europe equity benchmark to the corresponding countries or sectors.

7 Data are taken from Hain, Kölbel and Leippold (2022).
8 For tables showing the results for this analysis, see Bouchet and Schneider (2026a). Physical Climate Risk in the European Equity Market: Quantifying Country-Sector Heterogeneity.

This framework offers a basis for producing estimates of climate physical loss using a parsimonious, transparent and NGFS-aligned approach, but is not without caveat. We empirically show that estimated sensitivity parameters that structure the aggregate damage function in Step 1 are robust to the choice of NGFS scenario or integrated assessment model (IAM) and thus, scenario- and IAM-invariant.[9] This reflects the fact that IAMs operating under a given scenario must satisfy broadly similar aggregate carbon-budget constraints over the period. By contrast, while scenario selection is only modestly influential over outcomes over short time horizons (see the relatively narrow inter-scenario range depicted by the blue-shaded area circa-2050 in figure 1), it becomes highly influential over long time horizons (as one would perhaps expect from figure 1) since scenario-trajectories substantially diverge.

9 Parameters were estimated separately for each of the three IAMs that underpin the NiGEM outputs (GCAM 6.0 NGFS, MESSAGEix-GLOBIOM 2.0-M-R12-NGFS, and REMIND-MAgPIE 3.3-4.8) under each of the six NGFS Phase-V scenarios (Current Policies, Fragmented World, Delayed Transition, Nationally Determined Contributions, Net Zero 2050 and Below 2°C). Analysis also considered the degree of consistency between the scenario-based ranking of country-level vulnerability to physical climate risk and two widely used external benchmarks: the ND-GAIN Country Index and the Germanwatch Climate Risk Index. The objective was to evaluate whether countries identified as more climate-vulnerable in one system tend to occupy a similar position in the others. Overall, this demonstrated that the proposed ranking preserves the ordinal structure embedded in established climate-risk assessments. For more information, see Bouchet and Schneider (2026a).

Conclusion: from climate risk assessment to strategic investment decision-making

Investors are increasingly required to provide robust assessments of the potential impact of physical climate risks on their equity portfolios. We contend that (1) it is feasible to perform these assessments in a parsimonious and regulator-compliant manner, without the need for asset-level or physical hazard data that creates an excessive burden on resources; (2) that these assessments can be done in an operationalised manner, making them directly transferable to strategic investment decision-making. We believe that the framework presented here achieves both (1) and (2) simultaneously. Moreover, the findings generated from this framework strongly showcase the importance of portfolio construction (ie, accounting for the heterogeneous exposure of sectors and countries) in adjusting resilience to global temperature trajectories.

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Quantifying climate physical loss and heterogeneity Part 2: US equities

Vincent Bouchet, Director of ESG and Climate Research, Scientific Portfolio; **Nicolas Schneider**, Senior Research Engineer – Macroeconomist, EDHEC Climate Institute

How can we quantify the potential equity portfolio losses that may be attributed to physical climate risk in the future? Over recent years, it has become increasingly important for pension funds and other investors to answer this question in ways that are credible, transparent and in tune with regulators' requirements. In this article (a summary of a recent paper[1]), we examine the US equity market using a climate physical loss (CPL) framework. The methodology is top-down, parsimonious, based on public data, and aligned with the NGFS scenario set.[2] Importantly, it is also directly applicable to asset allocation and portfolio construction due to its use of a discounted cash-flow model and, therefore, of practical use to investors seeking not simply an assessment framework but a useable portfolio management tool.

This article explicitly focuses on US equities, while the accompanying article (Part I: European equities) investigates the case of European equities.

Key takeaways

We find that US states on average exhibit higher macroeconomic sensitivity to physical climate risks than Developed Europe, although there is a huge amount of heterogeneity between sectors and between states, with larger projected deviations of nominal GDP in southern regions (eg, –48.6% in Florida by 2100 under the NGFS current policy scenario).

However, the US cap-weighted equity benchmark displays a smaller CPL of –4.0%, versus –4.7% for Europe.

This apparent dampening effect is primarily driven by benchmark composition, with the US equity market more exposed to high-WACC, lower-sensitivity sectors and less concentrated in physically vulnerable regions than its European counterpart. As such, the research highlights the importance of portfolio construction in determining resilience.

Introduction: quantifying physical climate risk

Physical acute climate hazards such as heatwaves, floods, droughts, storms and/or chronic sea-level rise increasingly represent a challenge for firms and governments, as well as financially material risks for investors. Regulatory and supervisory authorities increasingly acknowledge that physical climate risks must be systematically integrated into risk management frameworks. The recommendations of the Task Force on Climate-related Financial Disclosures (TCFD), followed by the issuance of the International Sustainability Standards Board's IFRS S2 standard, have formalised the requirement to identify and disclose material physical and transition risks, underpinned by robust scenario analysis.

In the US, the regulatory treatment of climate-related financial risk remains more fragmented and contested than in the European Union, but supervisory authorities have nevertheless acknowledged that the risks may already be financially material and warrant forward-looking assessment. In March 2024, the Securities and Exchange Commission (SEC) adopted a climate-related disclosure rule requiring large public companies to disclose material climate risks and their financial impacts (SEC [2024]), though the rule has been stayed following legal challenges, leaving its implementation uncertain.[3]

In parallel with regulatory developments, an extensive academic literature has emerged to demonstrate how climate-related risks are reflected in asset

1 Bouchet, V., and N. Schneider (2026b). Physical Climate Risk in the U.S. Equity Market: Quantifying State-Sector Heterogeneity.

2 NGFS Scenarios Portal, Network for Greening the Financial System.

3 Reuters (2025). U.S. SEC Votes to Stop Defending Climate Disclosure Rules. 27 March.

prices and establish forward-looking methodologies such as short-term stress tests and long-term scenario analyses (which typically rely on integrated assessment models to quantify climate-related value-at-risk or evaluate changes in discounted cash flows under alternative temperature or policy pathways). However, these analyses are generally conducted at high levels of geographic and macroeconomic aggregation. While these are well suited for large systemic risk assessments, investors lack further information granularity for strategic investment management. This is particularly true when it comes to US states whose differential exposure to physical risk – although intuitive – is systematically averaged out by climate scenario providers (in search of national and global metrics).

As such, this article presents a methodology that is directly applicable to institutional investors and asset managers who are looking to understand CPL for their own equity portfolios. This approach has the advantage of providing intra-US answers through a transparent and intuitive framework, without imposing onerous or resource-intensive data requirements.

Building and calibrating a CPL framework

The proposed CPL framework rests on the principle that physical climate risk affects firm value through its impact on macroeconomic activity and, ultimately, on expected future cash flows. As such, a firm-level CPL is the difference between a firm's baseline enterprise value and an alternative valuation in which future cash flows are scaled by macroeconomic losses attributable to physical climate risks.

Formally, the procedure consists of three steps: (i) quantifying regional (country- and US state-level) GDP losses as a function of temperature anomalies; (ii) transmitting these losses to firm valuations through a discounted cash-flow framework; and (iii) reweighting relative valuation losses using sector-level sensitivity scores.

Step 1: estimating regional GDP losses as a function of temperature anomalies

Country- and US state-level macroeconomic projections are sourced to obtain both the baseline trajectory of aggregate economic activity and the deviations from this trajectory induced by temperature anomalies. Country-level deviations are based on the NGFS scenario set,[4] while state-level disaggregation (relating to each state's economic weight and exposure to physical climate risks) uses sub-national damage projection outputs from the EDHEC Climate-Induced Regional Macro-Impacts Projector (EDHEC-CLIRMAP) database.

The global non-linear effect of temperature on economic production has been empirically confirmed by Burke et al (2015) and Newell et al (2021), providing evidence for an inverted U-shaped relationship whereby temperatures exceeding a turning point generate amplifying reductions in per capita GDP. We first estimate a damage function at the most aggregated-level for the US (ie, national), linking physical risk-induced US-level GDP damages (arising from both chronic and acute climate risk) to a non-linear function of global temperature anomalies, as emulated by NGFS MAGICC across scenarios and IAMs,

$$\Delta y_{US,t} = \beta^{G}_{1,US}\Delta T_t + \beta^{G}_{2,US}\left(\Delta T_t\right)^2 + \varepsilon_{US,t}$$

where global temperature anomaly ΔT_t is measured relative to a reference year t_0 and where $\Delta y_{US,t}$ denotes the percentage deviation of real GDP from a no-damage baseline.

Because NGFS only provides estimates of GDP deviations relative to a baseline scenario at the country level, we introduce state-level heterogeneity through state-specific climate loss factors, thereby disaggregating national damages to the sub-national level. These climate loss factors correspond to the relative economic damage per US state related to the current state (not to a baseline scenario), as provided by an external database of macroeconomic damages: EDHEC-CLIRMAP.[5] This procedure is done to ensure maximum consistency between the NGFS US country damages and the regional damage.

Let L_s be the climate loss factor per state, and a time-varying calibration parameter θ_t,

$$\Delta y_{s,t} = \theta_t \cdot L_s$$

The calibration factor θ_t, is computed to ensure that the GDP-weighted sum of state damages equals the national damage estimated earlier:

$$\theta_t = \frac{\Delta y_{US,t}}{\sum_S w_s \cdot L_s}$$

Where $w_s = GDP_s / \Sigma_s GDP_s$ represents state s' share of total US GDP (20-year centred moving average). This approach ensures perfect aggregation ($\Sigma_s w_s \Delta y_{s,t} = \Delta y_{US,t}$) while allowing state damages to scale proportionally with their climate vulnerability factors. The calibration parameter varies over time, enabling the relative magnitude of state-level impacts to evolve with the US-level climate response.

From the estimated aggregate damage function, nominal GDP growth factors under the baseline and physical-risk scenarios are defined as

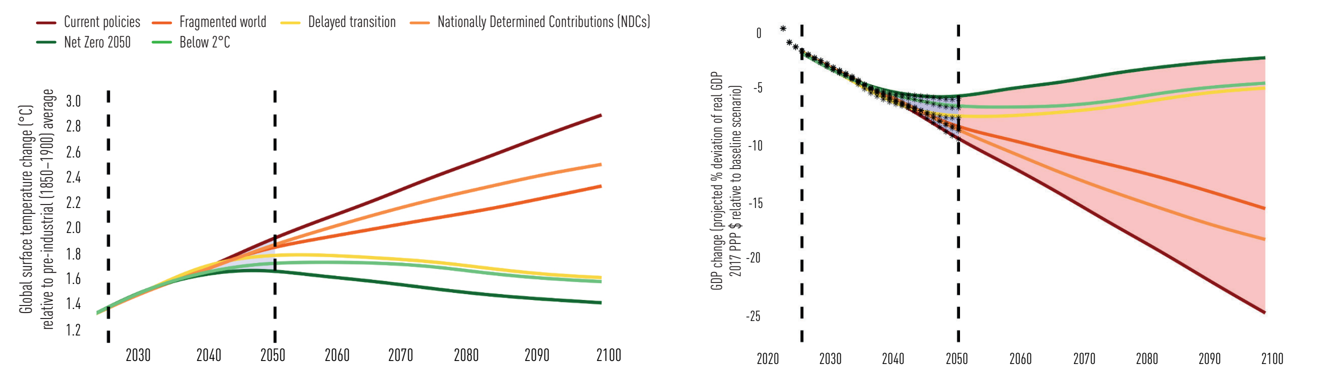
$$G^{base}_{s,t} = \frac{Y^{real,base}_{US,t}}{Y^{real,base}_{US,t0}} P_t, \quad G^{phys}_{s,t} = \frac{Y^{real,base}_{US,t}}{Y^{real,base}_{US,t0}}\left(1+\Delta y_{s,t}\right) P_t,$$

where P_t denotes the aggregate price level. These factors scale firm-level cash flows in the valuation stage.

4 The US economic sensitivity to a non-linear function of global temperature anomalies, $\beta^{G}_{1,i}$ and $\beta^{G}_{2,i}$ is estimated using the NGFS Phase 5 scenario dataset. This provides combinations of qualitative transition narratives and quantitative outputs from integrated assessment models (IAMs) that generate transition and physical-risk dynamics (eg, REMIND, MESSAGE). For each scenario–model configuration, the NGFS reports projected country-level paths of real GDP. Rather than using these GDP projections directly, the dataset is used to re-quantify the relationship between global temperature anomalies and deviations of country-level GDP from baseline. Long-horizon nominal GDP projections are derived from two components: (i) a baseline scenario that represents the path of economic activity in the absence of climate damages through 2100, and (ii) a physical-risk scenario in which global temperature anomalies are mapped into country-level economic losses. For long-term projections (post-2050), the baseline real-activity path combines projections from the NGFS and the IPCC–SSP2 framework. Country-level deviations are generated by applying the estimated damage coefficients to an exogenous global mean temperature (GMT) trajectory. The sequence of global temperature anomalies is inserted into the quadratic damage function above to obtain non-linear and country-specific GDP deviations $\Delta^{y}_{i,t}$. When combined with the baseline GDP trajectory, these deviations yield the physical-risk and baseline GDP growth factors, $G^{phys}_{i,t}$ and $G^{base}_{i,t}$, which in turn determine the evolution of firms' expected cash flows. For more information, see Bouchet and Schneider (2026a).
Physical Climate Risk in the United States Equity Market: Quantifying State-Sector Heterogeneity

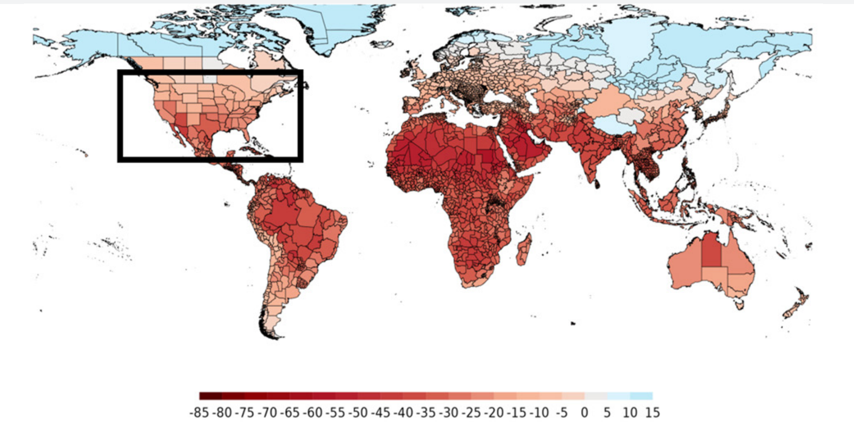
5 This is a proprietary EDHEC research building on Schneider (2025). Details on the quantitative methodology underlying this module are provided in §2.2 of that paper: Data and model calibration.

Figure 1. Global mean temperature scenario trajectories (left) and US GDP deviations across NGFS scenarios (right)



Data from NGFS, IPCC. Interpolation under GCAM 6.0 NGFS IAM. LHS: Global surface temperature (GSAT) projection from the MAGICCv7.5.3 climate model, based on AR6 climate diagnostics used by NGFS Phase-V. RHS: NiGEM-projected annual GDP changes from physical impacts for 2022–50 are represented by the stars. The GDP deviations obtained in this study, shown as continuous splines, ultimately coincide with those from NiGEM over the matching time frame, prior to extrapolation through 2100. For robustness check, GDP deviations are normalised to 2022 instead of the usual 2025 reference year.

Figure 2. Spatially distributed region-level projected damages % to per capita GDP, 2099



Data from EDHEC-CLIRMAP. Estimates from multi-model medians of 15 'likely' CMIP6 GCMs, epoch 2099 relative to historical 1985-2004 temperature means, according to a synthetic intermediate mid-point scenario between SSP5-8.5 vigorous & SSP2-4.5 moderate warmings. Projected damages across time (20-year centred moving averages, 2030–99) and geographies underpin the climate loss factor used in this article.
Source: Schneider (2025).

Step 2: Transmitting these losses to company valuations through a DCF model
The next stage is to incorporate those deviations into a discounted cash-flow (DCF) model: firm-level cash flows are assumed to grow with state nominal GDP and are discounted using sector-specific weighted average costs of capital (WACC).

The discount rates used in the discounted cash-flow model are obtained from Damodaran's publicly available estimates, which provide industry-level values for different regions.[6]

From a model construction perspective, we can let firms be indexed by j, and denote by $s(j)$ the country of firm j and by $k(j)$ its sector. Cash flows in the reference year t_0 are given by CF_{j,t_0}. For horizon t_0+1 to T, the baseline enterprise value follows[5]

$$EV_j^{base} = \sum_{t=t_0+1}^{T} \frac{CF_{j,t_0} \times G_{s(j),t}^{base}}{\left(1+r_{k(j)}\right)^{t-t_0}},$$

where $r_{k(j),i(j)}$ is the sector- and region-specific discount rate (weighted average cost of capital). Under the physical-risk scenario:

$$EV_j^{phys} = \sum_{t=t_0+1}^{T} \frac{CF_{j,t_0} \times G_{s(j),t}^{phys}}{\left(1+r_{k(j)}\right)^{t-t_0}},$$

Since CF_{j,t_0} is common to both valuations, the relative enterprise value loss simplifies to our primary impact metric,

$$EV_j^{rel} = \frac{\sum_{t=t_0+1}^{T} \frac{G_{s(j),t}^{phys}}{\left(1+r_{k(j)}\right)^{t-t_0}}}{\sum_{t=t_0+1}^{T} \frac{G_{s(j),t}^{base}}{\left(1+r_{k(j)}\right)^{t-t_0}}} - 1.$$

Thus, EV_j^{rel} measures the proportional decline in firm value solely attributable to physical climate damages.

Step 3: Reweighting relative valuation losses using sector-level sensitivity scores
In the third stage, a final adjustment is applied to reflect the prevailing market assessment of the sensitivity of different sectors to physical climate risk. Various ESG data providers report scores measuring sectors' perceived vulnerability to physical climate risk. Our model incorporates empirical evidence from Hain, Kölbel and Leippold (2022), who compare six firm-level physical risk scores from commercial and academic sources (figure 3). Although the providers differ markedly in methodology,

6 Firm-specific discount rates are computed by assigning each TRBC sector to the appropriate set of Damodaran industry classifications. Information on the sector and country classification of stocks is sourced from CIQ, while the portfolio weights of stocks are taken from the Scientific Portfolio Capital Weight Regional Benchmark for United States.
7 T is assumed to be far enough in the future to make any terminal value relatively negligible after discounting.

the authors document substantial systematic variation across sectors: utilities, energy and materials consistently appear as the most exposed sectors, while healthcare, communication services and information technology exhibit comparatively low exposure. This data is used to produce a sector-adjusted relative enterprise value loss, such that losses are scaled upward in highly exposed sectors and downward in less exposed sectors.[8]

Results: how exposed is the US market to physical climate risks?

Using the above model, we conducted empirical analysis focused on the 500 largest publicly listed US firms. This allowed us to assess:

- the heterogeneous climate physical risk sensitivity of US states;
- how sector-specific discount rates and sector-level exposure to physical hazards affect outcomes; and
- implications for US equity portfolio valuation.

Across the 50 US states, projected long-term economic outcomes exhibit substantial heterogeneity, ranging from an estimated gain of around 8% for Alaska to a loss of approximately 49% for Florida. These differences are strongly correlated with latitude: southern states face markedly larger economic losses, a pattern in good agreement with the general literature on this topic (Burke et al [2015]; Kalkuhl and Wenz [2020]; Linsenmeier [2023]; Kotz et al [2024]; Schneider [2025]; Bilal and Känzig [2026]).

Next, we look at sector-level heterogeneity. Sectors such as utilities or non-cyclical consumer – which typically exhibit relatively low WACC – are valued on the basis of long-term cash-flows and are therefore more exposed when the distant flows are impacted by physical risks. Conversely, high-WACC sectors such as technology are priced primarily on near-term cash flows, which makes their valuations less sensitive to physical risk shocks affecting distant cash flows. Incorporating this sectoral adjustment generates substantial dispersion in climate-induced valuation effects, with a ratio of approximately 1.6 between the most and least sensitive sectors (figure 5).

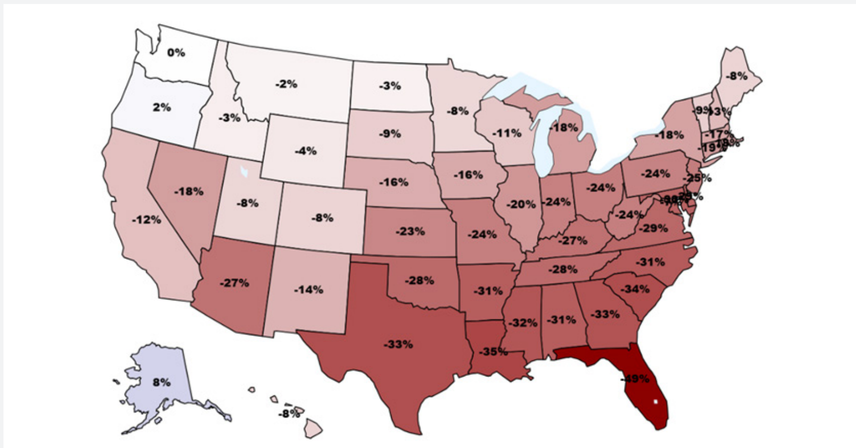
8 Again, for more details on the integration of these sensitivity scores into the enterprise value loss calculation, see Bouchet and Schneider (2026a). Physical Climate Risk in the United States Equity Market: Quantifying State-Sector Heterogeneity.

Figure 3. Sector-specific characteristics

Sector (TRBC)	S1	S2	S3	S4	S5	S6	avg_rank_k	$adj_k(\alpha = 0.2)$	$adj_k(\alpha = 0.5)$	r_k
Utilities	1	1	4	11	1	1	**3.2**	1.20	1.50	5.5%
Energy	4	2	1	7	5	4	**3.8**	1.16	1.39	7.0%
Basic materials	5	3	2	8	2	2	**3.8**	1.16	1.39	8.2%
Industrials	6	4	4	3	2	7	**4.8**	1.08	1.21	7.9%
Non-cyclical consumer*	7	5	5	4	8	3	**5.3**	1.05	1.12	6.6%
Cyclical consumer**	3	8	9	6	6	6	**6.3**	0.97	0.94	8.3%
Financials	11	9	3	1	7	8	**6.5**	0.96	0.90	6.5%
Technology	10	7	6	5	10	9	**7.8**	0.87	0.66	9.0%
Healthcare	9	6	7	10	9	11	**8.7**	0.80	0.50	8.6%
Telecoms	8	10	10	3	11	10	**8.7**	0.80	0.50	6.4%
*(Real estate***)*	*2*	*11*	*11*	*9*	*4*	*5*	*7.0*	-	-	

The first seven columns of this table are from Hain, Kölbel and Leippold (2022). They show sector rankings of six different ESG data providers based on the sensitivity of sectors to climate physical risks: Trucost (S1), Carbon4 Finance (S2), Southpole (S3), Truvalue Labs (S4), Sautner et al (S5) and Kölbel et al (S6).
* Consumer staples in Kölbel et al (2024), ** Consumer discretionary, *** Communication services, *** Original sector from Kölbel et al (2024), not covered in TRBC (included in financials).

Figure 4. Projected nominal GDP loss by 2100 under current policies for US states



The figure reports, for each US state, the projected relative loss in nominal GDP in 2100 under the NGFS current policies scenario (GCAM model), expressed as a percentage deviation from the corresponding baseline trajectory.

Figure 5. Effect of sector-specific discount rate only on climate physical loss

Country	Utilities	Financials	Non-cyclical consumer	Telecoms	Energy	Industrials	Cyclical consumer	Basic materials	Healthcare	Technology
Florida	17.4%	-15.4%	-15.2%	-14.9%	-14.0%	-12.3%	-11.8%	11.7%	-11.1%	-10.5%
Mississippi	-11.6%	-10.2%	-10.1%	-9.9%	-9.3%	-8.2%	-7.9%	-7.7%	-7.4%	-7.0%
Delaware	-10.3%	-9.1%	-9.0%	-8.8%	-8.3%	-7.3%	-7.0%	-6.9%	-6.6%	-6.2%
New Jersey	-8.8%	-7.8%	-7.7%	-7.5%	-7.1%	-6.2%	-6.0%	-5.9%	-5.6%	-5.3%
Kansas	-8.2%	-7.3%	-7.2%	-7.0%	-6.6%	-5.8%	-5.6%	-5.5%	-5.2%	-5.0%
Nevada	-6.6%	-5.8%	-5.7%	-5.6%	-5.3%	-4.7%	-4.5%	-4.4%	-4.2%	-4.0%
N Hampshire	-4.7%	-4.1%	-4.1%	-4.0%	-3.8%	-3.3%	-3.2%	-3.1%	-3.0%	-2.8%
Maine	-3.0%	-2.6%	-2.6%	-2.5%	-2.4%	-2.1%	-2.0%	-2.0%	-1.9%	-1.8%
Wyoming	-1.6%	-1.4%	-1.4%	-1.4%	-1.3%	-1.1%	-1.1%	-1.1%	-1.0%	-1.0%
Alaska	3.0%	2.7%	2.6%	2.6%	2.4%	2.1%	2.0%	2.0%	1.9%	1.8%

The heatmap displays the CPL for a selection of 10 US state–sector pairs after incorporating sector-specific discount rates. Sectors with low weighted average cost of capital tend to exhibit higher CPL as they are more sensitive to the long-term impact of climate change on their cash flows. Results are based on the NGFS current policies scenario, using the GCAM model at the 2100 horizon.

A second sectoral adjustment concerns the sectors' perceived vulnerability to physical climate risks: certain sectors are more vulnerable to physical risks (eg, utilities, energy and materials).[9] Because the initial degree of vulnerability is specified in terms of a ranking, its conversion into a valuation relies on an additional parameter α that can take different values to modulate the influence on the final CPL. As α is difficult to estimate empirically, the analysis evaluates the sensitivity of results to alternative values, focusing on α = 0.2 and α = 0.5 as plausible bounds. Results show that varying α not only alters the magnitude of CPL within a given state but may also change the ordering of the most affected sectors. This arises from the interaction with the discount-rate effect. For some sectors, such as utilities, a relatively low discount rate is compounded by high vulnerability (ie, a high adjustment factor) identified in the literature, whereas for other sectors, such as financials, the effect of a low discount rate is dampened by their relatively low perceived vulnerability to physical risks.[10]

Application to a US equity benchmark

Within the sample of US states and sectors, the estimated CPL spans a wide range, from –26.2% to +4.5% (adj_k(α = 0.5)). Portfolio-level exposure is therefore highly sensitive to the underlying region and sector allocation. For the US cap-weighted equity benchmark, the weighted CPL amounts to –4.0%. Figure 6 illustrates how alternative state- and sector-weightings would influence this result. It is evident that the benchmark's sector allocation highly mitigates physical risk exposure, and that this effect is amplified by the state-allocation effect. This latter can be traced back to the overweight positions in US states with lower physical-risk exposure.

This framework offers a basis for producing estimates of Climate Physical Loss for US equities through a parsimonious, transparent and NGFS-aligned approach, but is not without caveat.

We empirically show that estimated sensitivity parameters that structure the US aggregate damage function in Step 1 are robust to the choice of NGFS scenario or integrated assessment model (IAM) and thus, scenario- and IAM-invariant. This reflects the fact that IAMs operating under a given scenario must satisfy broadly similar aggregate carbon-budget constraints over the period. By contrast, while scenario selection is only modestly influential over outcomes over short time horizons (see the relatively narrow inter-scenario range depicted by the blue-shaded area circa-2050 in figure 1), it becomes highly influential over long time horizons (as one would perhaps expect from figure 1) since scenario-trajectories substantially diverge.

Figure 6. Climate physical loss of the US equity benchmark

Allocation	State allocation	Sector allocation	Weighted CPL
Equal state and equal sector (baseline)	Equal	Equal	–5.33%
Equal state and portfolio sector	Equal	Portfolio	–4.00%
Portfolio state and equal sector	Portfolio	Equal	–4.41%
US equity benchmark	**Portfolio**	**Portfolio**	**–3.97%**

The table reports the weighted climate physical loss under alternative allocations. Equal allocates identical weights to each of the 50 US states (or 10 sectors) in the sample, while Portfolio applies the weights of the US equity benchmark to the corresponding states or sectors.

Conclusion: from climate risk assessment to strategic investment decision-making

Investors are increasingly required to provide robust assessments of the potential impact of physical climate risks on their equity portfolios. We contend that (1) it is feasible to perform these assessments in a parsimonious and regulator-compliant manner, without the need for asset-level or physical hazard data that creates an excessive burden on resources; and (2) that these assessments can be done in an operationalised manner, making them directly transferable to strategic investment decision-making. We believe that the framework presented here achieves both (1) and (2) simultaneously. Moreover, the findings generated from this framework strongly showcase the importance of portfolio construction (ie, accounting for the heterogeneous exposure of sectors and economic regions distributed intra-country) in altering resilience to global temperature trajectories.

9 Data are taken from Hain, Kölbel and Leippold (2022).

10 For tables showing the results for this analysis, see Bouchet and Schneider (2026a). Physical Climate Risk in the United States Equity Market: Quantifying State-Sector Heterogeneity.

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Tackling the 'hidden ethics' in portfolio emissions calculations

Vincent Bouchet, Director of ESG and Climate Research, Scientific Portfolio

Investment industry participants have worked to establish a foundation for environmentally-focused investing that is grounded in science. Yet, when it comes to portfolio emissions and 'climate investing', even the most apparently science-based processes contain certain key decisions and steps that cannot be standardised based on scientific principles because they are irreducibly ethical in nature. Indeed, the heterogeneity of climate metrics and results – a challenge that continues to provoke calls for more uniformity – can often be traced, at least in part, to ethical differences. This article (a summary of a recent research paper[1]) addresses the 'hidden ethics' in portfolio emissions calculations and sets out a framework through which an investor might establish clarity and transparency for their ethical position.

Key takeaways

There are five methodological steps involved in the construction of a climate alignment metric. Ethical choices are particularly relevant at certain stages of the process, such as the allocation of the carbon budget.

Three different 'ethical investor' archetypes are proposed: the principled investor grounded in moral philosophy; the utilitarian investor maximising monetary utility under climate constraints; and the harmonist investor advocating for an extended scope of responsibility.

We model three alignment methodologies that would be consistent with these three ethical archetypes and use them to assess the greenhouse gas overshoot of a diversified equity portfolio (1,300 stocks). Results are similar at the portfolio level but very different at sector level, demonstrating the importance of these fundamentally ethical decisions.

Introduction: ethics are embedded in 'scientific' methodologies

Investors considering how to align equity portfolio 'emissions' with climate-related targets are immediately faced with a daunting reality: the significant heterogeneity among existing methodologies and their associated results.

ILB (2020), for example, found that implied temperature rise metrics for the same index varied between 1.5°C and 3°C depending on which approach was used, while correlations at the company level were weak or even negative. Points of differentiation included the scope of emissions considered, the carbon budget allocation, the reference scenarios and time horizons (Haalebos and Fouret [2022]; de Franco et al [2023]; Bouchet [2024]).

It would appear, at first glance, that standardisation of methodologies would be highly desirable. Indeed, many bodies have asserted that a consistent approach should be pursued (FOEN [2022]; GFANZ [2022a]; OECD [2022]). After all, a uniform approach would simplify comparisons across methodologies, enhance transparency for both institutional and retail investors, and facilitate regulatory assessments. Moreover, there is a widespread presumption that a 'science-based' approach should be able to produce a definitive and universally agreed way forward for all measurement methodologies.

However, the field continually resists efforts to achieve consensus. One of the reasons: decisions cannot be determined by scientific criteria alone and, as such, frequently rely on ethical choices (with which others may well disagree). Yet these

1 For an extended version of this analysis, see Bouchet, V. (2025). A Question of Ethics? Climate Alignment in Equity Portfolios.

Focus on emissions

An investor's impact on global warming primarily stems from the activities they finance, which may be negative (contributing to climate change) or positive (supporting mitigation).

In this article, we focus on the greenhouse gas (GHG) emissions of listed companies. Yet one can also consider other approaches using economic indicators (revenues and investments relating to sustainable activities) or governance and transition plans.

ethical foundations tend to be unspoken and are, as a result, insufficiently scrutinised. In this article, we assert that investors and industry practitioners should clearly define the ethical basis of their approach.

First, we examine five key methodological steps involved in constructing a climate alignment metric: choosing a reference scenario, defining allocation among companies, projecting company activity, measuring company alignment and aggregating alignment at the portfolio level. We show that most of the ethical decisions are related to the allocation of the carbon budget among companies within a sector.

Second, we review ethical frameworks that may inform the dilemmas associated with climate change mitigation. We also consider some political principles and agreements that have been developed in the context of climate change mitigation. Three ethical investor archetypes are derived: the principled investor grounded in moral philosophy; the utilitarian investor maximising monetary utility under climate constraints; and the harmonist investor advocating for an extended scope of responsibility.

Finally, we model three alignment methodologies that reflect these three ethical archetypes and assess the greenhouse gas overshoot (the projected excess emissions relative to a reference scenario) of a diversified equity portfolio holding the 1,300 largest publicly traded companies in developed markets. In this analysis, we find that the three different approaches produce quite similar results at the portfolio level, but a significantly different level of alignment within the most climate-relevant sectors. In particular, methodologies using production intensity rather than absolute emissions tend to reduce overshoot for companies in these sectors.

Where are the ethical choices in climate alignment metrics?

Developing portfolio alignment metrics involves a series of significant decisions. Some can be categorised as primarily scientific; others are more ethical in nature.

Despite some methodological variations, portfolio alignment metrics generally follow a common structure. Drawing from ILB (2020) and PAT (2021), we identify five key steps: (1) selecting a climate mitigation scenario as a reference, (2) allocating a carbon budget to companies, (3) projecting company emissions trajectories, (4) measuring alignment at the company level, and (5) aggregating company-level alignment into a portfolio-level metric. These steps are shown in figure 1.

For example, the 'level of ambition' of a target is tied to ethical questions of intergenerational fairness: investors seeking to choose between a 1.5°C or 2°C scenario must consider arguments from the likes of Caney (2016) that overly ambitious objectives could impose disproportionate costs on present generations, especially now that the likelihood of achieving 1.5°C has declined (UNEP [2024]), while a lack of action would impose unfair costs on future generations. The gap between the two scenarios is a large one from a practical standpoint: Lamboll et al (2023) estimate a remaining budget of 250GtCO_2 for a 1.5°C scenario (50% probability) versus 1,200GtCO_2 for 2°C, meaning that a 1.5°C-aligned budget for companies would be roughly five times smaller than that offered by a 2°C scenario. Investors might also wish to consider using a 1.5°C scenario for assessing past responsibility (since that target was historically more achievable) but use a 2°C to evaluate future alignment (such as an updated transition plan).

'Regional allocation', meanwhile, raises questions of interregional justice. This has been a politically high-profile subject for many years. Should wealthier nations, which have contributed disproportionately to greenhouse gas emissions since the Industrial Revolution, bear a greater responsibility for mitigation than developing countries with higher rates of poverty? While Nationally Determined Contributions (NDCs) do exist, reflecting current regional commitments and offering a political framework for distributing the remaining carbon budget among countries, these commitments do not necessarily align with relevant temperature rise pathways. As such, the investment industry is required to come up with

Figure 1. Portfolio alignment methodological steps and design choices

Step	Design choice	Options	Type of choice
1: Choosing a reference scenario	Consistency	No specific criteria/Science-based Targets Initiative (SBTi) criteria	Scientific
	Level of ambition	1.5°C/2°C/>2°C	Ethical
	Scenario update	Yes /No	Depends on goal of analysis
	Region allocation	Yes/No	Ethical
	Sector allocation	Yes/No	Scientific + ethical
2: Allocating carbon budget among companies	Scope of emissions	Scope 1/Scope 1+2 / Scope 1+2+3/Sector-specific scope	Ethical
	Emission metric	Absolute emissions/Emissions intensity (physical or financial)	Ethical
	Pace of reduction	Equal rate of reduction/Equal final performance (convergence)/ Proportional to activity (fair-share)	Ethical
3: Projecting company activity	Projection method	Constant/Historical trend/Based on company targets	Scientific
4: Measuring company alignment	Type of benchmark	Single scenario/Warming function	Scientific
	Alignment metric	Overshoot/Implied temperature rise	Depends on goal of analysis
	Horizon	2023–2100	Depends on goal of analysis
5: Aggregating company alignment at portfolio level	Aggregation method	Weighed average/Budget aggregation	Scientific

Note: The options available to each design choice are based on GFANZ (2022b) and Bouchet (2024) its own answers. To complicate matters, the existence of multinational corporations (who work in multiple regions but report aggregated data) makes it difficult to map emissions onto specific countries.

One of the most ethically dependent steps is the subject of how to allocate carbon budgets. For instance, when thinking about the scope of emissions, we can ask whether a company has a moral responsibility for activities outside of their direct control (such as indirect 'Scope 3' emissions). The answer to this question may even differ depending on the sector in question. After all, financial services company emissions predominantly fall into the Scope 3 category, while a company in the industrials sector may have a profile dominated by Scope 1 emissions. We might also ask whether to focus on absolute emissions, emissions intensity relative to monetary value, or emissions intensity relative to units of production. Here, too, there is an ethical angle: a utilitarian perspective might suggest simply maximising economic value added per ton of CO_2 emitted (Randers [2012]), while an egalitarian perspective could suggest allowing more emissions to companies producing 'essential' goods. In addition, we can consider the pace of reduction: should all firms target the same percentage reduction or not? Is it appropriate for firms to aim for the same end-point ('convergence,' as per Krabbe et al [2015])?

In short, the ethical questions raised in this process are primarily issues of distributional justice, such as intergenerational justice, interregional justice, and interpersonal justice. Repeatedly, one finds oneself asking: what are the responsibilities of current generations (as citizens, as investors, or both) to mitigate harm for future generations? Should rights to emit greenhouse gases be distributed evenly, without accounting for existing inequalities, the varying capabilities of individuals or companies to reduce emissions, or the 'value' of the emissions-generating activities? Distributional justice carries through into an investment portfolio management context in terms of the degree of emissions that an investor is willing to accept from each company or sector.

Three 'ethical investor' archetypes

How, then, can these ethical questions be answered in a coherent manner? Investors might turn to legislation, regulation, political commitments and non-binding agreements from a variety of national and supranational entities. After all, politics is the mechanism through which modern societies chiefly determine how ethical burdens are to be weighed and acted upon. Yet, while various agreements, laws and principles have provided guidance on specific aspects of climate mitigation[2], they do not succeed in providing a genuinely prescriptive approach that investors can (or should!) follow without needing to make choices of their own.

As such, we must look for an intrinsic foundation for ethical decisions. Here, it may be helpful to review a few schools of thought:

Pragmatism: A philosophical perspective that emphasises the practical consequences of ideas, focusing on their applicability to real-world problems. Key intellectual figures in this strand include Charles Sanders Peirce and John Dewey. Dewey advocated experimentation and adaptability, emphasising that ethical questions – and efforts to improve – should originate from lived experiences. Pragmatism has been mobilised to address global societal challenges, offering alternative frameworks for organisations to collaborate on complex and uncertain issues such as climate change (Ferraro et al [2015]). In our view, pragmatism should be an overarching criterion for investors when addressing the subject of climate mitigation, since real-world applicability is key to any successful implementation. Suboptimal but actionable methodologies may be preferable to ideals, especially given the urgency of climate change mitigation over the near term.

Kantian ethics: An ethical theory that emphasises universal moral duties, founded on the work of Immanuel Kant and other Enlightenment philosophers. The approach is centred on the concept of the categorical imperative: the principle that individuals should act only according to maxims that could consistently be applied by all others as a universal law. Kantian ethics focuses primarily on the intentions and principles behind actions rather than their consequences: what makes an action 'good' is the intention rather than the outcome.

Utilitarianism: A school of thought arguing that actions are morally right if they maximise overall well-being, ie, if they achieve the greatest good for the greatest number. Key thinkers include Jeremy Bentham and John Stuart Mill. By prioritising the future and outcomes, utilitarianism would advocate for policies and technologies that not only facilitate immediate reductions in emissions but also deliver substantial long-term benefits relative to their costs.

Egalitarianism: A political and moral philosophy grounded in the principle that all individuals are fundamentally equal in worth. Its origins can be traced back to Enlightenment thinkers such as Jean-Jacques Rousseau. More recently, egalitarianism has been developed by John Rawls, whose A Theory of Justice (1971) introduced the concept of justice as fairness, advocating for the distribution of resources to benefit the least advantaged. Rawls' framework, grounded in the "original position" and the hypothetical "veil of ignorance" (designing a society without at first knowing the role that one will play in it), seeks to ensure that social arrangements are structured to uphold equality of opportunity and mitigate arbitrary inequalities.

Imperative of responsibility: Articulated by Hans Jonas in 1979, this strand of thought is a response to the unprecedented power of modern technology. Jonas critiques traditional ethics as being inadequately prepared to address the long-term and global consequences of technological advancements, particularly their potential to harm future generations and the natural world. Drawing on the existential philosophy of Heidegger, Jonas proposes an imperative of responsibility, calling on us to act in a way that preserves the conditions for life on Earth. This

2 To name a few, these include: the Paris Agreement, which establishes legally binding commitments to limit global warming to well below 2°C above pre-industrial levels with efforts to keep it to 1.5°C, including Nationally Determined Contributions (NDCs) that outline each country's voluntary emission reduction targets; the EU Taxonomy or the Sustainable Finance Disclosure Regulation (SFDR), which creates collectively agreed standards regarding metrics specific to financial institutions; the Precautionary Principle (UN World Charter for Nature [1982]); the Principle of Common but Differentiated Responsibilities and Respective Capabilities (UN Framework Convention on Climate Change [1992]).

forward-looking ethical framework emphasises caution and accountability, asserting that the vulnerability of nature and the interests of unborn generations demand a radical extension of our moral horizon.

Based on these ethical frameworks and the prior discussion of ethical considerations involved when determining alignment metrics, we introduce three ethical investor archetypes, each of them corresponding to a certain configuration of the alignment model (figure 2).

Figure 2. Ethical investor archetypes

	'Principled'	'Utilitarian'	'Harmonist'
Basis	Traditional moral philosophy, particularly Kant's categorial imperative.	Maximisation of monetary utility; 'greatest good for the greatest number'.	Egalitarian principles and concept of 'responsibility'
Example of application	Simple and universal principles that, if adopted by all, would achieve climate mitigation objectives.	Companies generating higher revenue may receive larger carbon budget (greater economic contribution).	All firms should contribute to mitigation. Focus on emissions intensity per unit of production in critical sectors.

Figure 3. Alignment model configuration for three ethical investor archetypes

Alignment model configuration		Ethical investor achetypes		
Methodological step	**Design choice**	**Principled investor**	**Utilitarian investor**	**Harmonist investor**
1: Choosing a reference scenario	Consistency	Science-based Targets Initiative criteria		
	Level of ambition	1.5°C (IEA Net Zero Emissions scenario)		
	Scenario update	Yes (2023)		
	Region allocation	No		
	Sector allocation	No	Yes	Yes
2: Allocating carbon budget among companies	Scope of emissions	Scope 1	Scope 1+2	Sector-specific
	Emission metric	Absolute emissions	Emissions intensity (financial unit)	Emissions intensity (physical unit)
	Pace of reduction	Equal rate of reduction	Proportional to activity (fair-share)	Equal final performance (convergence)
3: Projecting company activity	Projection method	Based on company targets if consistent with historical trend		
4: Measuring company alignment	Type of benchmark	Single scenario		
	Alignment metric	Overshoot		
	Horizon	2050		
5: Aggregating company alignment at portfolio level	Aggregation method	Budget aggregation		

Figure 3 shows an adjusted version of the alignment model presented in figure 1. In this version, the three ethical investor archetypes translate into different decisions at certain choices. These are not the only steps with ethical dimensions, of course: for example, the 'level of ambition' remains the same for all three variants. In addition, the specific decisions indicated – while aligned with the ethical archetype (as discussed below) – do not represent the only decisions that could be consistent with that stance. Nonetheless, this illustrative exercise and the modelling that follows help to show the significance of the relevant choices.

Here, the principled investor approach is grounded in traditional moral philosophy, particularly Immanuel Kant's categorical imperative. It emphasises simple and universal principles that, if adopted by all companies, would ensure the achievement of climate mitigation objectives. Consequently, such an investor does not differentiate between sectors and prioritises Scope 1 emissions, as these fall directly under a company's control. Absolute emissions (rather than intensity) are in focus and the reduction target is uniform across all companies.

The utilitarian investor, meanwhile, seeks to maximise monetary utility and, therefore, prioritises emissions intensity relative to revenue rather than absolute emissions. This philosophical perspective would also strongly suggest retaining Scope 1 and Scope 2 emissions (consistent with the prevailing conventions in institutional climate frameworks) in the analysis. The allocation of the carbon budget is based on the monetary value added by each company: companies generating higher revenue today receive a larger carbon budget, as their economic contribution is deemed to enhance overall utility. This also implies that the pace of emissions reductions is determined in relation to current revenue.

Finally, the harmonist investor approach is rooted in egalitarian principles. This perspective advocates an extended scope of responsibility, incorporating Scope 3 emissions when relevant. The harmonist investor focuses on emissions intensity per unit of production in critical sectors. In distributing the decarbonisation effort across companies, the approach acknowledges differences in initial emissions levels while emphasising the necessity for all firms to contribute to mitigation. Consequently, this approach adopts the principle of reduction and convergence, ensuring both absolute reductions and a gradual alignment of emissions intensities across companies.

Analysing a diversified equity portfolio

In order to illustrate the potential effects of the alignment model choices outlined in figure 3, we examined a portfolio of the 1,300 largest publicly traded developed market companies by market capitalisation worldwide, approximately aligning with the MSCI World index constituents.[3]

At portfolio level, all three alignment models result in similar 'overshoot' (approximately 110%, see figure 4): emissions trajectories would result in a cumulative carbon budget between 2022 and 2050 that is approximately twice as large as would be required for alignment with the NZE pathway. However, when examining sectors with particularly high climate relevance, substantial discrepancies emerge between the three approaches.

For instance, under the principled investor approach outlined above, which focuses on Scope 1 emissions and allocates carbon budget based on an equal reduction rate across companies, the airlines sector exhibits an overshoot of

3 In all cases, the reference scenario is the Net Zero Emissions (NZE) pathway developed by the International Energy Agency (IEA) in 2023. Company-level emissions, activity data, and climate targets are sourced from ISS and Moody's. For further details on models and data, please see Bouchet (2025).

Figure 4. Impact of ethical choice on portfolio overshoot

Sector	Weight	Stocks	Principled investor			Utilitarian investor			Harmonist investor		
			Trajectory	Benchmark	Overshoot	Trajectory	Benchmark	Overshoot	Trajectory	Benchmark	Overshoot
Oil and gas	2.82%	36	386,962	167,753	**131%**	414,012	213,194	**94%**	2,686,003	2,024,614	**33%**
Automotive	2.09%	17	2,859	1,405	**103%**	7,196	3,220	**124%**	306,001	208,092	**47%**
Electricity	1.73%	40	467,086	261,166	**79%**	474,994	204,982	**132%**	622,791	463,088	**34%**
Aluminium	0.03%	2	10,796	4,215	**156%**	20,350	10,606	**92%**	22,392	10,737	**109%**
Airlines	0.04%	7	16,920	6,468	**162%**	16,974	12,897	**32%**	18,166	20,171	**-10%**
Steel	0.13%	6	59,808	31,016	**93%**	73,911	50,462	**46%**	97,002	50,686	**91%**
Shipping	0.06%	5	14,483	8,332	**74%**	14,547	11,397	**28%**	24,683	15,721	**57%**
Other	88.13%	1170	668,444	288,116	**132%**	927,185	401,246	**131%**	19,814,757	8,318,512	**138%**
Portfolio	**95.04%**	**1283**	**1,627,358**	**768,472**	**112%**	**1,949,169**	**908,003**	**115%**	**23,591,795**	**11,111,623**	**112%**

Notes: This table represents, for each ethical approach and by sector, the aggregate emission trajectory (proection), the aggregate emission benchmark (aligned with the reference scenario), and the resulting overshoot.

162%. In contrast, the harmonist investor approach, which prioritises emissions intensity per unit of production (emissions per passenger-kilometre for airlines), results in a negative overshoot of -10% for the same sector.[4]

This pattern arises primarily because an intensity-based framework does not account for potential growth in production that could drive absolute emissions upwards. Many companies within climate-sensitive sectors exhibit physical emissions intensities close to the trajectory required for net-zero alignment (making them aligned under the harmonist investor framework) but their absolute emissions have increased alongside production growth (making them non-aligned from the principled investor perspective). As such, a harmonist investor would theoretically be able to maintain a larger allocation to airlines than a principled investor when seeking to achieve their alignment pathway.

Conclusion: time to clarify ethical foundations

Ethical choices are embedded in portfolio emissions alignment metrics. While scientific considerations can guide certain methodological choices, such as scenario selection and emissions projections, much of the necessary parameterisation sits on moral – not scientific – foundations. Moreover, as we have shown, different ethical schools of thought result in very different alignment results at sector and company level for real-world equity portfolios.

These findings underscore the need for transparency. Rather than striving for a single, standardised, apparently scientific approach in this space, the investment management industry should be clarifying and communicating the ethical foundations of their decisions and models – empowering investors with the tools and the information to make choices that reflect their own defined values while ensuring methodological rigour.

4 These intensity-based results for companies belonging to climate-relevant sectors should be interpreted with caution due to the limited number of companies within each sector in the sample. Additionally, potential biases may arise from the fact that the sample includes the largest firms within each sector.

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393, Promenade des Anglais
BP3116
06202 Nice Cedex 3
France
Tel +33 (0)4 93 18 99 66

24 avenue Gustave Delory
CS 50411
59057 Roubaix Cedex 1
France
Tel +33 (0)3 20 15 45 00

16–18 rue du 4 septembre
75002 Paris
France
Tel +33 (0)1 53 32 76 30

10 Fleet Place, Ludgate
London
EC4M 7RB
United Kingdom
Tel +44 (0)20 7332 5600

1 George Street
#15-02
Singapore 049145
Tel +65 (0)6438 0030