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Physical Climate Risk in the European Equity Market: Quantifying Country – Sector Heterogeneity

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Abstract

This paper develops a parsimonious, scenario-analysis framework to quantify climate physical loss (CPL) for listed firms and equity portfolios. CPL is defined as the valuation loss arising from climate-induced physical damage, obtained by scaling future cash flows with country-level economic deviations derived from damage functions. The framework embeds these macroeconomic losses within a discounted-cash-flow model using sector-specific discount rates and vulnerability adjustments. Applying the methodology to 423 large European firms and a Developed Europe equity benchmark reveals strong cross-country and cross-sector heterogeneity in exposure to physical climate risk, as well as a portfolio-level loss of roughly –4.7% under a "current policy" scenario. Results are robust across integrated assessment models but sensitive to scenario–horizon choices. This framework, drawing exclusively on publicly available data, delivers a transparent and supervisory-aligned approach to assessing physical climate risk and informing strategic asset allocation.

Key Takeaways

- Projected physical-risk GDP losses by 2100 vary widely across Europe, from about –28% in Spain to modest gains in Finland, closely matching established vulnerability indices.

- Differences in discount rates and vulnerability scores generate substantial dispersion in valuation impacts, with a sensitivity ratio of roughly 1.6 across sectors.

- The Developed Europe equity benchmark exhibits a CPL of approximately –4.7%, with results robust to model specification but sensitive to the scenario–horizon combination.

Keywords: Physical Climate Risk, Equity Market.

1. Introduction

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1. Introduction

Global temperature records have been broken with unsettling regularity in recent years. According to the Copernicus Climate Change Service, the global mean temperature over January–November 2025 is already 1.48°C above the 1850–1900 pre-industrial baseline, such that 2025 is currently tied with 2023 as the second-warmest year on record, behind 2024. Over the 2023–2025 period, the three-year average temperature is projected to exceed 1.5°C for the first time, consolidating a regime in which chronic warming and more frequent extreme events are now structural. Physical acute climate hazards such as heatwaves, floods, droughts, storms and or chronic sea-level rise increasingly represent a challenge for households, firms and governments, as well as a potential source of financial risk for investors.

Regulatory and supervisory authorities increasingly acknowledge that physical climate risks are financially material and therefore must be systematically integrated into risk management frameworks. The recommendations of the Task Force on Climate-related Financial Disclosures, 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. Within the European Union, the Sustainable Finance Disclosure Regulation and the Corporate Sustainability Reporting Directive render such disclosures mandatory for institutional investors and large corporations, and supervisory bodies have begun to operationalise these expectations.

For example, 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. At a broader level, the Network for Greening the Financial System (NGFS) has developed a harmonised scenario framework and methodological guidance for the assessment of long-term physical and transition risks, reinforcing supervisory expectations that climate-related financial risks be evaluated using forward-looking methodologies.

In parallel with these regulatory developments, an extensive academic literature has emerged on how climate-related risks are reflected in asset prices. Campiglio et al. (2023) synthesise evidence that both transition and physical risks affect equity, bond, loan, and real-estate valuations, while also concluding that these risks are unlikely to be fully priced. Backward-looking studies, relying on historical disaster events or policy announcements, document significant revaluations around climate-related news, but are inherently constrained by the short history of observable climate shocks. Forward-looking methodologies therefore play a central role. Campiglio et al. (2023) classify these approaches into short-horizon stress tests – which impose severe but stylised shocks to portfolios – and long-term scenario analyses that trace the impact of plausible emission and temperature pathways over several decades. Long-horizon assessments typically rely on integrated assessment models (IAMs) to quantify climate-related value-at-risk or to evaluate changes in discounted cash flows under alternative temperature or policy pathways. Major contributions include Dietz et al. (2016), Battiston et al. (2017), and, more recently, Mandel et al. (2025). This literature consistently documents that climate-related damages may be economically and financially material at horizons extending beyond 2030. However, these

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analyses are generally conducted at a high level of aggregation, making them well suited to systemic risk assessment but less informative for investor-level strategic asset allocation.

This paper introduces a top-down framework to quantify climate physical loss (CPL) for listed firms and diversified equity portfolios, aligned with the scenario architecture of the NGFS. CPL measures the valuation loss attributable to climate-induced physical damages, defined as the difference between a baseline enterprise value and an alternative valuation in which future cash flows are scaled by macroeconomic losses. The framework draws on NGFS Phase V scenarios, combining chronic damage functions from Kotz et al. (2024) with acute-risk estimates from historical natural-disaster data, but does not rely directly on NGFS GDP paths. Instead, it re-estimates country-specific quadratic damage functions linking deviations from baseline GDP to global temperature anomalies, allowing projections to extend to 2100 and reducing dependence on individual integrated assessment models. These GDP deviations are incorporated into a discounted-cash-flow model in which firm-level cash flows grow with national nominal GDP and are discounted using sector-specific weighted average costs of capital. A final sectoral adjustment introduces heterogeneity in perceived vulnerability, using cross-provider rankings from Hain, Kölbel and Leippold (2022) to scale losses upward in highly exposed sectors and downward in sectors assessed as less exposed.

Three principal empirical findings arise from the analysis of 423 large publicly listed firms across fifteen European countries and the corresponding Developed Europe equity benchmark. First, physical climate risk displays pronounced heterogeneity across countries. Under the NGFS current policy scenario, projected deviations of nominal GDP in 2100 range from approximately −28% in Spain to modest gains in Finland, with systematically larger output losses in Southern Europe. These spatial patterns exhibit strong concordance with established vulnerability indicators, including the ND-GAIN Index and the Germanwatch Climate Risk Index, as reflected in high rank correlation coefficients. Second, sector characteristics exert a substantial influence on CPL. Cross-sectoral differences in weighted average cost of capital (WACC) generate a ratio of approximately 1.6 between the most and least exposed sectors, and the inclusion of sector-specific vulnerability scores further amplifies this dispersion. Third, at the portfolio level, the Developed Europe equity benchmark exhibits a weighted physical climate loss of approximately −4.7%. Sensitivity analyses indicate that these results are robust with respect to the choice of integrated assessment model but more sensitive to the joint selection of climate scenario and time horizon, consistent with the inertia of the climate system and the increasing divergence of long-run temperature trajectories.

For asset owners and asset managers, the proposed framework offers two principal advantages. First, it is intentionally parsimonious: the CPL measure is derived from publicly available data and is implemented within a standard discounted-cash-flow valuation framework. This facilitates its direct application to strategic asset allocation and benchmark construction, without necessitating detailed information on physical hazards or asset-level data. Second, it is consistent with prevailing supervisory expectations for long-term climate scenario analysis, thereby creating a link between regulatory stress-testing methodologies and portfolio valuation.

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The remainder of the paper is structured as follows. Section 2 outlines the development of country-specific damage functions and the accompanying valuation model. Section 3 presents the empirical findings. Section 4 reports robustness checks and sensitivity analyses. Section 5 concludes and discusses the implications for investors and regulatory bodies.

2. Model and Data

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2. Model and Data

The proposed framework quantifies a CPL, defined as a valuation loss attributable to physical climate risks, by mapping macroeconomic damage projections to firm-level enterprise value within a discounted cash flow model. All macroeconomic inputs and physical risk parameters are calibrated to the scenario set published by the NGFS, thereby ensuring methodological alignment with prevailing supervisory and regulatory practices.

2.1 Model

Physical climate risk affects firm value through its impact on macroeconomic activity and, ultimately, on expected future cash flows. In the proposed methodology, climate-induced physical damages reduce country-level economic output, which in turn proportionally scales the expected cash flows of firms domiciled in the affected country. Firm value under the physical-risk scenario is then obtained by discounting these adjusted cash flows at a sector-specific discount rate. An additional sector-level adjustment is applied to reflect the prevailing market assessment of heterogeneous sectoral sensitivity to physical climate risks. The comparison of this stressed valuation with its corresponding baseline (no-damage) valuation yields the firm-level physical climate loss.

Formally, the procedure consists of three steps: (i) estimating regional 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.

Regional Economic Losses from Temperature Anomalies

The global non-linear effect of temperature on economic production[1] has been empirically confirmed in Burke et al. (2015) and Newell et al. (2021), providing evidence for an inverted U-shaped relationship[2], whereby temperatures exceeding a turning-point generate amplifying reductions in per capita GDP. We follow this literature and estimate a quadratic damage function at the country level linking global temperature anomalies and GDP damages – arising from both chronic and acute[3] climate physical risk impacts,

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

where $\Delta y_{i,t}$ denotes the percentage deviation of real GDP in country i from a no-damage baseline,

$$\Delta y_{i,t} = \frac{Y^{real,dam}_{i,t} - Y^{real,base}_{i,t}}{Y^{real,base}_{i,t}}$$

Global temperature anomaly ΔT_t is measured relative to a reference year t_0. Because damages are expressed as deviations from a climate-neutral baseline, the regression contains no intercept. Implicitly, output in the reference year already embeds historical climate effects.

1 - Derivations on high-weather dependent sectors can be found in Schlenker and Roberts (2009), Burke and Emerick (2016), Auffhammer et al. (2017), and Auffhammer (2018).
2 - Knowledge on the relationship between anthropogenic emissions, rising temperatures, and macroeconomic damages has recently converged towards general principles. Until about 15 years ago, damages (Ω, measured as the percentage deviation of GDP relative to a reference scenario or baseline) were derived from largely global macroeconomic assessments, offering little information on their geographic distribution. The DICE model (Dynamic Integrated model of Climate and the Economy), developed by Nordhaus in the 1990s, was among the first IAMs and served as a methodological reference for many subsequent models. Nordhaus' enumerative approach (1991) laid the groundwork for DICE and related IAMs, though models such as FUND and PAGE were developed independently with different structures. Early IAM approaches and later Weitzman (2010) faced criticism for using damage functions that lacked empirical or theoretical support (Pindyck, 2013) which posed empirical validation challenges. Burke et al. (2015), mentioned above, is among the very first empirical approach through panel econometric methods linking annual per capita GDP series to plausibly exogenous fluctuations in average temperature.
3 - This element is further detailed in 2.2.

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

$$G_{i,t}^{\text{base}} = \frac{Y_{i,t}^{real,base}}{Y_{i,t0}^{real,base}} P_t, \qquad G_{i,t}^{\text{phys}} = \frac{Y_{i,t}^{real,base}}{Y_{i,t0}^{real,base}} (1 + \Delta y_{i,t}) P_t, \quad (2)$$

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

Firm value under baseline and physical-risk scenarios

Let firms be indexed by j, and denote by $i(j)$ 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[4]

$$EV_j^{base} = \sum_{t=t_0+1}^{T} \frac{CF_{j,t_0} \times G_{i(j),t}^{base}}{\left(1 + r_{k(j),i(j)}\right)^{t-t_0}}, \quad (3)$$

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

$$EV_j^{\text{phys}} = \sum_{t=t_0+1}^{T} \frac{CF_{j,t_0} \times G_{i(j),t}^{phys}}{\left(1 + r_{k(j),i(j)}\right)^{t-t_0}}. \quad (4)$$

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

$$EV_j^{\text{rel}} = \frac{\sum_{t=t_0+1}^{T} \frac{G_{i(j),t}^{phys}}{\left(1 + r_{k(j),i(j)}\right)^{t-t_0}}}{\sum_{t=t_0+1}^{T} \frac{G_{i(j),t}^{base}}{\left(1 + r_{k(j),i(j)}\right)^{t-t_0}}} - 1. \quad (5)$$

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

Incorporating Sector-Specific Sensitivity to Physical Climate Risk

To reflect heterogeneous market perceptions of climate sensitivity across sectors, a sector-specific adjustment factor is constructed. Several independent sources of information – corresponding to separate environmental, social and governance (ESG) data providers – each report a score measuring the sensitivity of every sector to physical climate risk. For each provider, these sectoral scores are converted into a within-provider ranking. Let avg_rank_k denote the mean of these rankings for sector k across all providers. This average rank is then normalised to the unit interval:

$$norm_k = \frac{avg\_rank_k - \min_l avg\_rank_l}{\max_l avg\_rank_l - \min_l avg\_rank_l}. \quad (6)$$

Higher performance (lower rank) receives a stronger upward adjustment by inverting the scale:

$$norm_k^{inv} = 1 - norm_k.$$

4 - T is assumed to be far enough in the future to make any terminal value insignificant after discounting.

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These scores are linearly mapped into the interval [1-α,1+α], where α controls the amplitude of the adjustment:

$$adj_k = (1-\alpha) + 2\alpha\, norm_k^{inv}.$$

The sector-adjusted relative enterprise value loss for firm *j* is therefore:

$$EV_j^{\mathrm{adj}} = EV_j^{\mathrm{rel}} \times adj_{k(j)}. \quad (7)$$

2.2 Data and Model Calibration

The model is calibrated on three complementary categories of data. First, country-level macroeconomic projections characterise both the baseline trajectory of aggregate economic activity and the deviations from this trajectory induced by temperature anomalies. Second, sector-level measures of the WACC are employed to discount projected cash flows within the valuation framework. Third, sector-specific indicators of perceived sensitivity to physical climate risk, constructed from multiple ESG data providers, are used to modulate the relative valuation losses across industries.

Estimation of country-level economic loss sensitivity to temperature anomalies

The country-specific sensitivities to a non-linear function of global temperature anomalies, $\beta_{1,i}^{G}$ and $\beta_{2,i}^{G}$ in equation (1), are estimated using the NGFS Phase 5 scenario dataset. This dataset provides combinations of qualitative transition narratives (e.g., Delayed Transition, Net Zero 2050, Current Policies), and quantitative outputs from IAMs that generate the associated transition and physical-risk dynamics (e.g., REMIND, MESSAGE). For each scenario–model configuration, the NGFS reports projected country-level paths of real GDP. Rather than using these GDP projections directly as measures of economic loss, the dataset is employed to empirically re-quantify the relationship between global temperature anomalies and deviations of country-level GDP from baseline. The re-estimation strategy is motivated by three main considerations. First, it enables the extension of GDP-loss projections to 2100 – beyond the NGFS horizon limited to 2050, by leveraging global temperature anomaly trajectories available up to the end of the century. Second, it reduces dependency on any single integrated assessment model by extracting structural multi-model sensitivities rather than using model-specific GDP outputs. Third, it facilitates the use of alternative climate scenarios – such as those from the IPCC – by mapping our global temperature trajectories with theirs whenever they provide them, thereby ensuring consistency across scenario families and providers.

In the NGFS framework, estimates of economic damages from physical climate risks combine two principal sources of information: (i) regional projections of chronic physical-risk damages from Kotz et al. (2024), and (ii) estimates of relative economic losses from acute physical risks derived from a historical natural-disaster database reporting country-level damage statistics for events such as floods, storms, and droughts (EM-DAT). The regional projections of chronic physical-risk damages – based on Kotz et al. (2024) – is a major contribution of the most recent release (Phase-V) of NGFS scenarios.

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Kotz et al. (2024) construct projections of chronic physical risk-driven net economic damages by combining (1) economic sensitivities to climate drivers estimated over sub-nationally historical data, with (2) an ensemble of future climate change simulations of daily climate data[5]. Net damages here correspond to the sum of the individual, sometimes offsetting, effects from five distinct climate drivers: average temperature, temperature variability, precipitation totals, precipitation extremes and number of wet days.

(1) Gross Regional Product (GRP) sensitivities to the climate fluctuations are econometrically quantified by linking sub-nationally reported gross regional economic outputs per capita[6] of 1,661 provinces in 88 countries to plausibly exogenous[7] weather fluctuations over the period 1979–2019[8] in a global panel fixed-effect (Fes) model with *N* and *M* lagged variables, whether temperature or precipitation (respectively) presented in equation (8) below:

$$\begin{gathered} g_{\{r,y\}} = \mu_r + \eta_y + k_r y + \\ \sum_{L=0}^{N}\left(\alpha_{1,L}\Delta\bar{T}_{r,y-L} + \alpha_{2,L}\Delta\bar{T}_{r,y-L}\cdot\bar{T}_r\right) + \sum_{L=0}^{N}\left(\alpha_{3,L}\Delta\tilde{T}_{r,y-L} + \alpha_{4,L}\Delta\tilde{T}_{r,y-L}\cdot\hat{T}_r\right) + \\ \sum_{L=0}^{M}\left(\alpha_{5,L}\Delta P_{r,y-L} + \alpha_{6,L}\Delta P_{r,y-L}\cdot P_r\right) + \sum_{L=0}^{M}\left(\alpha_{7,L}\Delta PWD_{r,y-L} + \alpha_{8,L}\Delta PWD_{r,y-L}\cdot PWD_r\right) + \\ \sum_{L=0}^{M}\left(\alpha_{9,L}\Delta Pext_{r,y-L} + \alpha_{10,L}\Delta Pext_{r,y-L}\cdot\bar{T}_r\right) + \epsilon_{r,y} \end{gathered} \tag{8}$$

Where $g_{\{r,y\}}$ denotes the annual, regional GRP per capita growth rate, measured as the first difference of the logarithm of real GRP per capita in region *r* at time *y*; μ_r is a region fixed effect (captures time invariant characteristics of region r); η_γ is year fixed effect (captures global time trends common to all regions); $k_r y$ is region specific linear time trend coefficient (captures secular regional growth time trends). This specification uses interactions of the climate variables with their historical average (1979–2019) baseline to account for regionally varying effects of climate identified in previous work (Kalkuhl and Wenz, 2020). Standard errors are clustered at the region-level. $\Delta\bar{T}_{r,y-L}$ and $\Delta\tilde{T}_{r,y-L}$ respectively denote the first difference of average temperature and temperature variability in deg. C for region r and year *y*, lagged by L (and up to *N*) years; $\bar{T}_r$ and $\hat{T}_r$ correspond to the time-invariant long-run averages of temperature and temperature variability for region r and computed over the historical estimation period; $\Delta P_{r,y-L}$, $\Delta PWD_{r,y-L}$ and $\Delta Pext_{r,y-L}$ respectively denote the change in total precipitation (mm), precipitation extremes (summed precipitation in mm beyond the 99.9th percentile of historical (1979–2019) yearly precipitation) and number of wet days (where precipitation exceeds 1mm) for region r and year y, lagged by L (and up to M) years. Finally, $\epsilon_{r,y}$ is the error term (idiosyncratic shocks orthogonal to physical risks and correlated with GRP growth) for region *r* at time y; α_i, L are the coefficients of interest to be estimated by this model.

5 - Climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) that have been bias-adjusted, downscaled, and harmonised within the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) framework to ensure consistency and comparability across climate-impact models.
6 - From Wenz et al. (2023)'s MCC-PIK Database of Sub-national Economic Output.
7 - See Pretis (2021) on why climate fluctuations can be considered exogenous predictors of economic outputs and thus be relied on for causal identification in climate economics.
8 - From the W5E5 dataset, which combines the WATCH Forcing Data methodology applied to ERA5 reanalysis (WFDE5) with bias correction from the European Centre for Medium-Range Weather Forecasts Reanalysis v5 (ERA5), as implemented by the ISIMIP and provided on a 0.5° × 0.5° daily resolution grid.

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(2) The ISIMIP-processed CMIP6 dataset[9] provides projections of future 2 m temperature and precipitation totals from 21 distinct Global Climate Models (GCMs) simulated under the Coupled Model Intercomparison Project Phase VI (CMIP6) whose outputs are bias-corrected and downscaled to a 0.5° grid from 2015 to 2100. For each physical risk factor, local-day climate projections (i.e., simulations of climate change-driven shifted average weather conditions) were truncated to the geographic extents and frequency of the GRP realisations and used to calculate variables – consistent with those in the historical estimation dataset – for years in the historical (1979–2019) and future epochs (2025, 2026, …, 2099) under a high (RCP8.5) and a low (RCP2.6) greenhouse gas emission scenario. Taking the inter-epoch difference between historical and future climate averages yields a climate "Delta" for each physical risk factor.

Kotz et al. (2024)' projected GRP deviations from chronic physical risks were ultimately obtained by combining (1) with (2); i.e., (1) the set of climate Deltas corresponding to *L* climate anomaly trajectories by SSP-RCP combination and embedding climate model uncertainty, with (2) the global physical risk-GRP response functions empirically estimated on historical economic and climate data.

Resulting projections of chronic physical damages are spatially aggregated from region- to country-year using a gridded population density-weighting method, prior to being incorporated into the NiGEM econometric model as smooth, scenario-specific reductions in total factor productivity (TFP), capturing persistent, long-run disruptions to economic activity. By contrast, acute physical risks are introduced as stochastic shocks to TFP, designed to represent short-run macroeconomic effects of extreme events. The NGFS then aggregates the chronic and acute components into a unified, country-level damage function and maps these damages to trajectories of global mean temperature anomalies. The final output, provided as is in the NGFS NiGEM dataset[10], is $\Delta y_{i,t}$. Labelled GDP change from physical, it thus embeds both acute and chronic dimensions – although it is important to mention that this latter one substantially dominates.

The country-specific sensitivities to global temperature anomalies, $\beta_{1,i}^{G}$ and $\beta_{2,i}^{G}$, are obtained by estimating a pooled specification that interacts temperature anomalies with time-invariant country indicators:

$$\Delta y_{i,t} = \sum_{i} [\beta_{1,i}^{G} C_i \, \Delta T_t + \beta_{2,i}^{G} C_i \, (\Delta T_t)^2] + \varepsilon_{i,t},$$

where $\Delta y_{i,t}$ denotes the percentage deviation of real GDP for country i from its baseline, and C_i is a country dummy. The resulting vector of coefficients $\beta_{1,i}^{G}$ and $\beta_{2,i}^{G}$ are therefore country-specific but invariant across time and scenario narratives. For the reasons mentioned above, estimated beta parameters of $\Delta y_{i,t}$ from equation (9) confer the methodological benefit of concentrating information from NGFS Phase-V and its underlying benchmark studies. Therefore, for the chronic side physical risks, $\beta_{1,i}^{G}$ and $\beta_{2,i}^{G}$ actually capture information on (i) economic geography (i.e., aggregation of region damages by country via a weighting method accounting for heterogeneous intra-country distribution of projected damages); (ii) the multi-dimensional and persisting nature of physical risks (i.e., sum of the individual effect of each climate factor plus the integration of enhanced constraint on the persistence of climate

9 - See https://data.isimip.org/ (repository) and https://gmd.copernicus.org/articles/12/3055/2019/ (academic reference).
10 - https://www.ngfs.net/ngfs-scenarios-portal/data-resources

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impacts on output up to N=10 and M=4 lags for temperature and precipitation variables respectively); and climate model uncertainty (i.e., derivation of projected damages using a large ensemble of anomaly trajectories).

Long-Term Scenarios

The long-horizon nominal GDP projections are derived from two components: (i) a baseline scenario that represents the counterfactual 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 using the country-specific damage coefficients estimated in equation (9).

The baseline real-activity path combines projections from the NGFS and the IPCC–SSP2 framework. Real GDP from 2025 to 2050 is taken from the NGFS Phase 5 baseline scenario, which provides annual GDP generated by the GCAM integrated assessment model. Beyond 2050, the trajectory is extended using projections from the IPCC–SSP2 "Basic Drivers" dataset[11]. More precisely, the SSP2 long-run GDP dynamics are extracted from the OECD ENV-Growth model. These projections initially reported at five-year intervals are interpolated to annual frequency and chained to the NGFS level in 2050 to ensure a smooth and internally consistent continuation of the real GDP path. Nominal GDP is then obtained by combining this real-output trajectory with a price index constructed from annual NGFS inflation rates over 2025–2050 (inflation beyond 2050 is held constant at the average rate observed between 2040 and 2050).

Country-level deviations from this baseline under physical climate risk are generated by applying the estimated damage coefficients to an exogenous global mean temperature (GMT) trajectory. The main scenario considered in the empirical analysis presented in the Results section is the NGFS "Current Policies", because it is the most likely to occur (Rebonato and Melin, 2025). The associated GMT series, produced by the GCAM integrated assessment model, is interpolated to annual frequency and recentred to express temperature anomalies relative to the reference year (2023). Given that climate change is a long-stochastic warming process that follows an upward trend globally (Dell et al., 2014), the uncertainty introduced by such interpolation is minimised. Exhibit 1 shows the GMT scenario trajectories after linear interpolation under GCAM 6.0 NGFS. A visual inspection of this graph suggests that the cross-scenario distribution of GMT trajectories is relatively narrow circa 2050, before divergence occurs over 2050-2100.

This sequence of global temperature anomalies is inserted into the quadratic damage function of equation (1) 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, $\mathbf{G}_{i,t}^{\mathbf{phys}}$ and $\mathbf{G}_{i,t}^{\mathbf{base}}$, which in turn determine the evolution of firms' expected cash flows.

11 - SSP2 represents a "middle-of-the-road" socioeconomic pathway characterised by moderate population and productivity growth, limited inequality, and an absence of major structural shocks.

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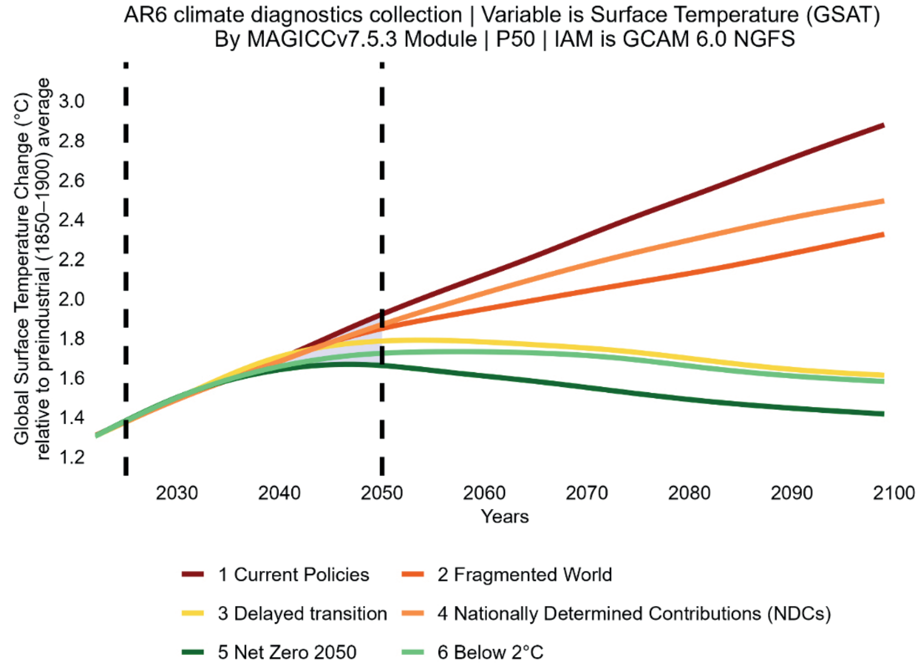
Exhibit 1: Global mean temperature scenario trajectories



Notes: P50 denotes the median percentile of the global surface temperature (GSAT) projection from the MAGICCv7.5.3 climate model, based on AR6 climate diagnostics used by NGFS Phase-V. Blue shaded area shows the cross-scenario distribution of GMT circa 2050.

Sector-Specific Weighted Average Cost of capital

The discount rates used in the discounted cash flow model are obtained from Damodaran's publicly available estimates of the WACC, which provide industry-level values for different regions, including Europe. Firm-specific discount rates are computed by assigning each Thomson Reuters Business Classification (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.

Sector-Specific Climate Physical Risk Sensitivity Perception

To account for heterogeneity in sector vulnerability to physical risks, the model incorporates empirical evidence from Hain, Kölbel, and Leippold (2022), who compare six firm-level physical risk scores from commercial and academic sources (Exhibit 2). 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 Health Care, Communication Services, and Information Technology exhibit comparatively low exposure.

Within the valuation framework, these rankings are used to adjust the country-driven loss estimates derived from the temperature-damage model. Since the macroeconomic channel captures only the transmission from aggregate GDP losses to firm cash flows, the sectoral adjustment introduces additional heterogeneity aligned with observed cross-provider consensus on sector sensitivity.

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Exhibit 2: Sector-specific characteristics

Sector (TRBC)	S1	S2	S3	S4	S5	S6	avg_rank_k	adj_k (α=0.2)	adj_k (α=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%
Health Care	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	-	-	

*Notes: The seven first columns of this table 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), which estimates exposure using geolocation of physical assets combined with climate hazard mapping under RCP scenarios; Carbon4 Finance (S2), which integrates climate hazard ratings with firm-level vulnerability metrics and distinguishes between direct and indirect hazards; Southpole (S3), which assesses exposure through a combined sectoral and geographic approach incorporating vulnerability indicators; Truvalue Labs (S4), which derives a climate-risk signal from news and social-media content using natural language processing and sentiment analysis; Sautner et al. (S5), which constructs an academic score based on the frequency of climate-related terms in earnings-call transcripts; and Hain, Kölbel, and Leippold (2022) (S6), which employs a BERT-based model to identify disclosures of climate risk in firms' regulatory 10-K filings. *Consumer staples in Kölbel et al. (2022), **Consumer Discretionary, ***Communication Services, *** Original sector from Kölbel et al. (2022), not covered in TRBC (included in Financials).*

3. Results

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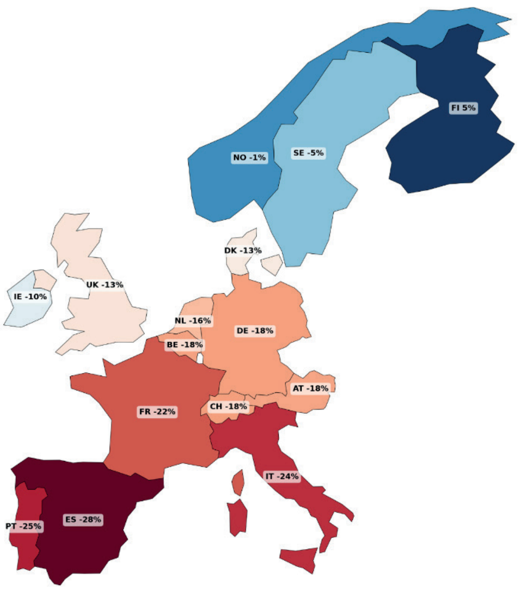
3. Results

The empirical analysis is conducted on a sample of 423 large publicly listed firms headquartered across fifteen European countries. The discussion proceeds in three steps. First, the cross-country heterogeneity in estimated climate-risk sensitivities is examined. Second, the role of sector-specific discount rates and sector-level vulnerability to physical hazards is assessed, highlighting their contribution to cross-sectional dispersion in outcomes. Finally, the implications for a regionally diversified equity portfolio are evaluated to illustrate how aggregate exposures to climate physical risks may propagate through portfolio-level valuations.

3.1 Country-Level Economic Sensitivity to Climate Physical Risks

The estimates for $\beta^G_{1,i}$ and $\beta^G_{2,i}$ are reported in Exhibit 10 of the Appendix. The fully interacted model in equation (9) yields an adjusted $R^2$of 0.9 for the total pool of countries. A sequential estimation of a country-level version of equation (9) enables the derivation of a separate adjusted R^2 for each cross-sectional unit. For purposes of internal consistency and diagnostic assessment, this set up facilitates more transparent hypothesis testing across countries. It enables the assessment, country by country, (i) that the variance in the dependent variable $\Delta y_{i,t}$ is more effectively captured by the non-linear representation of global temperature anomalies (rather than by a linear alternative); and (ii) that the advantageous properties of estimated $\beta^G_{1,i}$ and $\beta^G_{2,i}$, namely country-specific, scenario- and IAM-invariant, empirically hold. Results from this robustness test are presented in 4.1.

Exhibit 3: Projected nominal GDP loss in Europe by 2100 under current policies



Notes: 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.

Among the 15 countries considered, only Finland exhibits positive but small coefficients, indicating that warming may generate limited economic gains for this high-latitude economy. This geographic gradient is further illustrated when projecting country-level GDP losses in 2100 using the estimated parameters (Exhibit 3). Three clusters emerge. 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

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3. Results

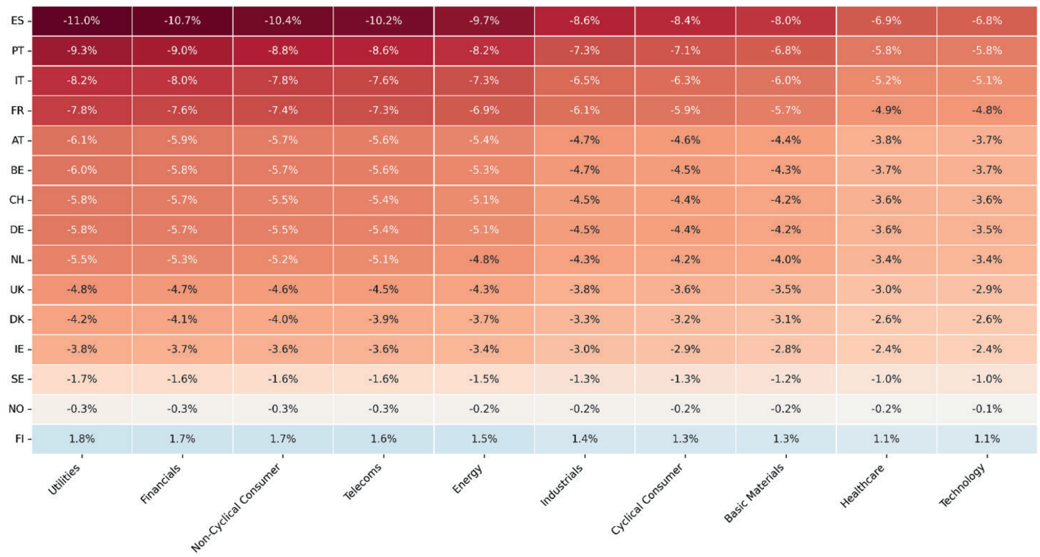
Belgium, Germany, Switzerland, and Austria, exhibits relatively homogeneous losses between 18% and 19%. By contrast, the southern economies incur substantially larger declines, with France, Italy, Spain, and Portugal all exceeding a 20% relative GDP loss by 2100.

A second region-specific 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 magnifies 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 further amplifies the present value of their projected CPLs (Exhibit 13, Appendix).

3.2 Sector-Specific Discounting and Vulnerability Effects

Building on the country-level sensitivity to physical climate risks, the model incorporates two sector-specific adjustments. The first relates to heterogeneity in the WACC (Exhibit 2). Because projected physical damage generally rises over time, sectors characterised by low discount rates experience a stronger reduction in the present value of future cash flows. 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 these distant flows are affected by climate hazards. Conversely, high-WACC sectors such as Technology are priced primarily on near-term cash flows, which makes their valuations less sensitive to long-horizon climate impacts. Incorporating this first sectoral adjustment generates substantial dispersion in climate-induced valuation effects within a given region, with a ratio of approximately 1.6 between the most and least sensitive sectors (Exhibit 4).

Exhibit 4: Effect of sector-specific discount rate only on CPL



Notes: The 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.

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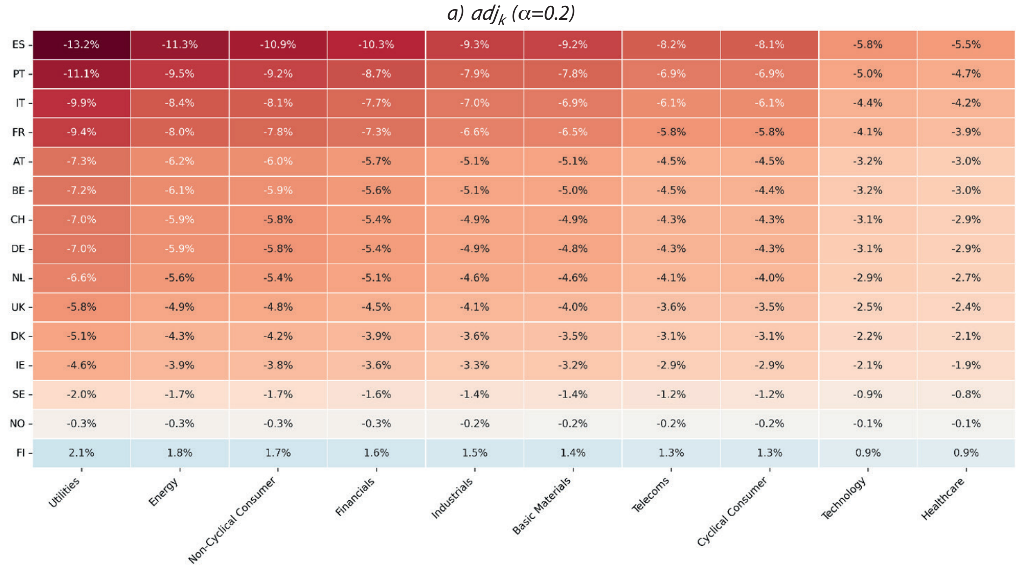
3. Results

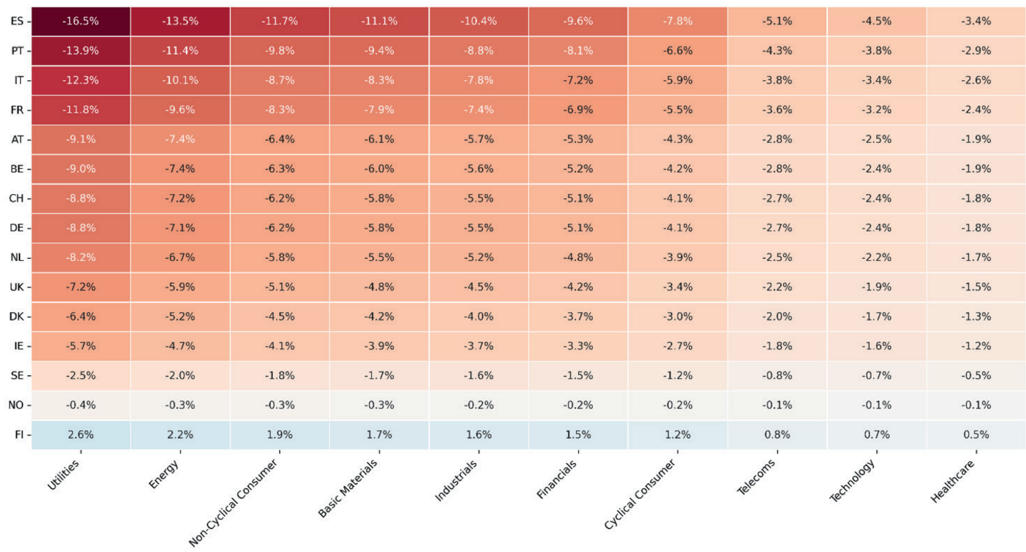
The second sectoral adjustment concerns the sectors' perceived vulnerability to physical climate risks. Sectors identified by Hain, Kölbel, and Leippold (2022) as being more vulnerable to physical risks (e.g., Utilities, Energy, and Materials) are associated with comparatively larger losses than sectors assessed as less exposed (e.g., Health Care, Communication Services, and Information Technology). Because the initial degree of vulnerability is specified in terms of a ranking, its conversion into a valuation relies on a 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 to cover a meaningful interval.

Exhibit 5: Combined effect of sector discount rate and vulnerability on CPL

a) adj_k *(*α*=0.2)*



b) adj_k *(*α*=0.5)*



Notes: The heatmaps display the CPL for each country–sector pair after incorporating both sector-specific discount rates and sectoral vulnerability to physical climate risks. For the vulnerability adjustment, two values of the scaling parameter α (0.2 and 0.5) are reported to reflect uncertainty regarding its magnitude. Results are based on the NGFS "Current Policies" scenario, using the GCAM model at the 2100 horizon.

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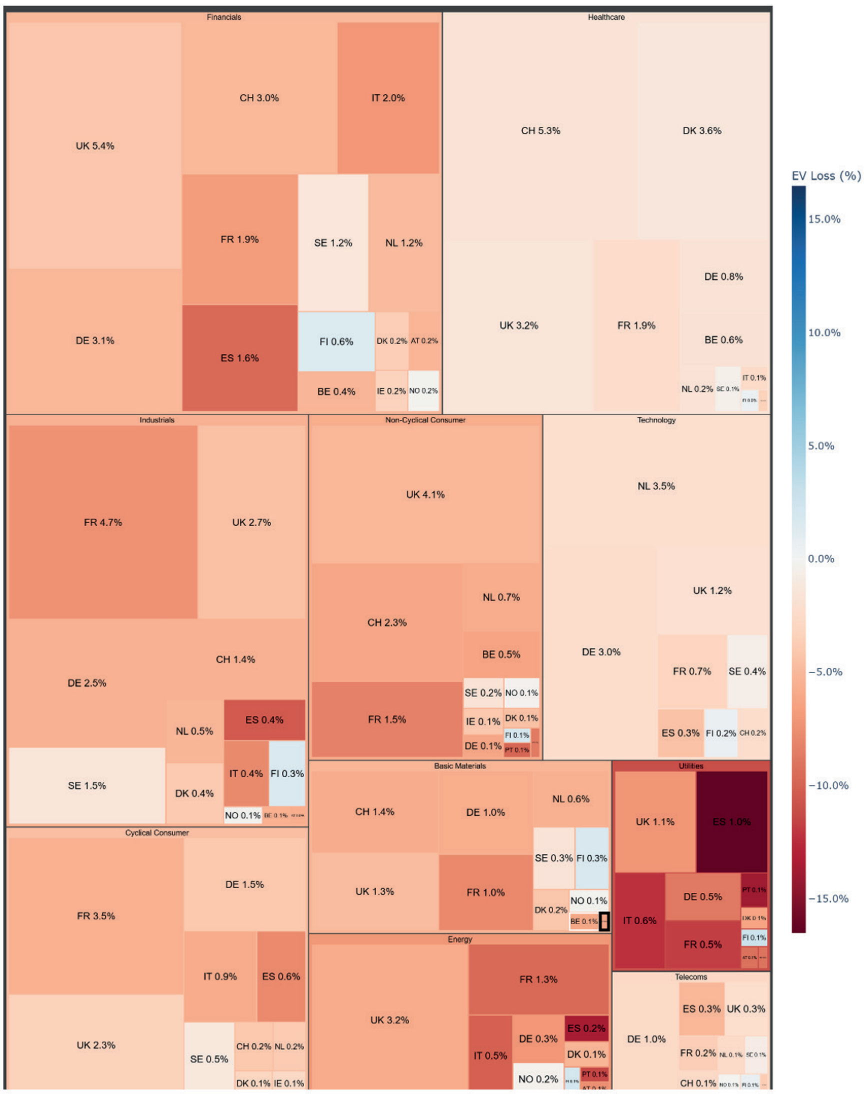
3. Results

Results show that varying α not only alters the magnitude of CPL within a given region 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 (i.e., a high adjustment factor), 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. Consequently, when α is increased from 0.2 (implying that some sectors incur 0.8 times the baseline economic loss while others incur 1.2 times) to 0.5, the relative position of the Financials sector in the ranking of CPLs declines substantially (Exhibit 5).

3.3 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%. 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%. Exhibit 6 highlights the distribution of country-sector allocation jointly with the corresponding vulnerability levels.

Exhibit 6: Sector and country allocation of the Developed Europe equity benchmark



Notes: The figure displays the joint country–sector composition of the Developed Europe equity benchmark alongside each segment's estimated physical climate loss. Rectangle size reflects the benchmark weight of each country–sector, while colour intensity represents the corresponding CPL value (from lower losses in light tones to higher losses in darker tones).

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3. Results

Exhibit 7 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[12]. This decomposition shows that the benchmark's sector allocation modestly mitigates climate exposure, but that this beneficial sector effect is more than offset by a negative country-allocation effect, driven by overweight positions in countries with higher physical-risk exposure.

Exhibit 7: CPL of a diversified Developed Europe equity benchmark

Allocation	Country allocation	Sector allocation	Weighted CPL
Equal Country & Equal Sector (Baseline)	Equal	Equal	-4.46%
Equal Country & Portfolio Sector	Equal	Portfolio	-4.18%
Portfolio Country & Equal Sector	Portfolio	Equal	-4.93%
Developed Europe equity benchmark	**Portfolio**	**Portfolio**	**-4.67%**

Note: The table reports the weighted 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.

12 - The interaction between country and sector weights contributes an additional +0.03 percentage points.

4. Robustness Check and Sensitivity Analysis

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4. Robustness Check and Sensitivity Analysis

The structural nature of the framework implies sensitivity to several assumptions, particularly those related to the underlying input data. This section first reviews the extent to which NGFS-based GDP damage estimates align with established proxies for country-level vulnerability to climate change, and subsequently evaluates the sensitivity of the CPL results to the choice of horizon, scenario, and integrated assessment model.

4.1 Country-Level Economic Loss

First, the analysis verifies empirically that the estimated sensitivities $\beta_{1,i}$ and $\beta_{2,i}$ are not driven by the choice of scenario or IAM. To this end, parameters are 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). For each country i, the benchmark coefficients $\beta_{1,i}$ and $\beta_{2,i}$ are systematically evaluated against a set of 18 IAM- and scenario-specific parameters. The empirical evidence presented in Exhibit 11 of the Appendix indicates that the resulting coefficients are consistent across IAMs and scenarios in terms of sign, magnitude, and statistical significance, suggesting that the estimated sensitivities are stable and thus robust to model choice. Uncertainty is thus minimised, as underlined by the narrow inter-coefficient range by country.

Secondly, the analysis assesses the degree of consistence between the scenario-based ranking of country-level vulnerability to physical climate risk and two widely used external benchmarks: the ND-GAIN Country Index, which measures national adaptive capacity and institutional readiness, and the Germanwatch Climate Risk Index, which reflects realised physical losses over 1995–2024. The ND-GAIN Index is routinely employed by regulators, including ESMA and the Banque de France, to characterise the vulnerability of financial exposures.

Given that these indicators differ in scale and measurement units, the comparison is conducted on an ordinal basis. The objective is to evaluate whether countries identified as more climate-vulnerable in one system tend to occupy a similar position in the others. Pairwise associations are measured using Spearman's ρ and Kendall's τ, which capture, respectively, monotonic dependence and the probability of concordant ordering across country pairs. The results indicate strong alignment: Spearman correlations reach $\rho = 0.768$ with ND-GAIN and $\rho = 0.889$ with Germanwatch, and the corresponding Kendall statistics confirm this pattern. For instance, the estimated $\tau = 0.733$ between the scenario-based ranking and Germanwatch implies that country pairs are ordered consistently 73.3% more often than would occur by chance. Overall, the evidence shows that the proposed ranking preserves the ordinal structure embedded in established climate-risk assessments.

The correspondence becomes even clearer when countries are grouped into three categories based on their projected GDP loss in 2100. Among "high-risk" countries – those with losses exceeding 20% - the set of most exposed countries coincides exactly with the Germanwatch ranking and matches three of

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4. Robustness Check and Sensitivity Analysis

the four in ND-GAIN (France being assessed as less exposed in ND-GAIN). A similar pattern emerges for "low-risk" countries - defined as losses below 18% – where five out of the six countries classified as low-risk appear in each alternative system (Exhibit 8).

Finally, the joint consistency of the three rankings is evaluated using Kendall's coefficient of concordance (W), a non-parametric statistic that summarises agreement among multiple rankers. Kendall's W takes values between 0 (no agreement) and 1 (perfect concordance), and is computed from the dispersion of summed ranks across countries. The estimated value, W = 0.869, is notably high and indicates that the three systems, despite relying on distinct conceptual foundations (adaptive capacity, historical realised impacts, and scenario-based macroeconomic losses), produce highly consistent country orderings.

Exhibit 8: Comparison of country-level climate vulnerability rankings across metrics

Risk category	Country	GDP loss 2100	Rank GDP	Rank ND-GAIN	Rank CRI
High Risk	Spain	-28%	**1**	2	3
	Portugal	-25%	**2**	3	4
	Italy	-24%	**3**	1	2
	France	-22%	**4**	7	1
Medium Risk	Austria	-18%	**5**	8	9
	Belgium	-18%	**6**	4	6
	Switzerland	-18%	**7**	13	10
	Germany	-18%	**8**	9	5
Low Risk	Netherlands	-16%	**9**	6	8
	United Kingdom	-13%	**10**	10	7
	Denmark	-13%	**11**	12	11
	Ireland	-10%	**12**	5	12
	Sweden	-5%	**13**	11	13
	Norway	-1%	**14**	15	14
	Finland	5%	**15**	14	15

Note: This table compares the country-level physical climate vulnerability used in this paper with two external reference rankings. Our ranking is based on the GDP-loss ranking (Column "Rank GDP") is derived from the projected decline in country-level output under the physical-risk scenario and forms the basis for the three proposed risk categories (High, Medium, Low). The ND-GAIN ranking (University of Notre Dame) measures countries' structural vulnerability and adaptive capacity, with higher ranks indicating more resilient and better-prepared economies. The CRI ranking (Germanwatch Climate Risk Index) reflects historical exposure and losses from acute climate-related disasters over 1995–2024, with lower ranks denoting higher historical impact. Cells highlighted in light grey indicate countries for which a given external ranking would assign a different risk category than the one implied by the GDP-loss metric. Despite some local discrepancies, the three systems exhibit strong overall consistency, particularly at the top of the distribution: the set of high-risk countries is stable across methodologies.

4.2 Sensitivity to Horizon, Scenario and Model

One motivation for estimating GDP sensitivities to global temperature deviations is to enable the use of alternative temperature trajectories associated with different time horizons, models, and climate scenarios. Exhibit 9 illustrates that the resulting CPL, whether computed at the country-sector, or portfolio level, exhibits heterogeneous sensitivity to these modelling choices. The choice of integrated assessment model exerts only a limited influence on CPL estimates. This likely reflects the fact that global

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4. Robustness Check and Sensitivity Analysis

temperature pathways are tightly linked to cumulative GHG emissions, and that IAMs operating under a given scenario must satisfy broadly similar aggregate carbon-budget constraints over the period.

By contrast, scenario selection becomes increasingly influential as the horizon extends. Differences across scenarios have minimal effects at the 2050 horizon but generate substantial divergence when the horizon is extended to 2100. This pattern reflects the inertia of the climate system: substantial shifts in mitigation pathways - for example, moving from current policies to a net-zero scenario - have limited short-term implications for temperature but produce large differences over longer horizons. Accordingly, the critical determinant of CPL estimates is the joint choice of horizon and scenario. At 2050, neither scenario nor model selection materially alters outcomes, whereas at 2100 scenario choice dominates. This pattern can be attributed to the widening range of GDP deviations observed post-2050 (see Exhibit 12 in the Appendix), which can be ultimately traced back to structural differences in global temperature trajectories (see Exhibit 1). Identifying which temperature and emissions trajectories are most plausible is therefore important but is left to future research.

Exhibit 9: CPL sensitivity to horizon, scenario and model

Horizon	Scenario	Integrated Assessment Model	(ES) Healthcare	(ES) Utilities	(FI) Healthcare	(FI) Utilities	(Europe) Portfolio
2050	Current Policies	GCAM	-1.8%	-6.2%	0.3%	1.0%	-2.1%
		MESSAGE	-1.8%	-6.3%	0.3%	1.0%	-2.1%
		REMIND	-2.1%	-7.5%	0.3%	1.2%	-2.6%
	Fragmented World	GCAM	-1.7%	-5.9%	0.3%	0.9%	-2.0%
		MESSAGE	-1.8%	-6.4%	0.3%	1.0%	-2.2%
		REMIND	-2.0%	-6.8%	0.3%	1.1%	-2.3%
	Net Zero	**GCAM**	**-1.4%**	**-4.6%**	**0.2%**	**0.8%**	**-1.6%**
		MESSAGE	-1.5%	-5.0%	0.2%	0.8%	-1.8%
		REMIND	-1.2%	-4.0%	0.2%	0.7%	-1.4%
2100	Current Policies	GCAM	-3.4%	-16.5%	0.5%	2.6%	-4.7%
		MESSAGE	-3.4%	-15.8%	0.5%	2.5%	-4.5%
		REMIND	-3.9%	-18.5%	0.6%	3.0%	-5.3%
	Fragmented World	GCAM	-2.7%	-11.9%	0.4%	1.9%	-3.6%
		MESSAGE	-2.8%	-11.6%	0.4%	1.9%	-3.6%
		REMIND	-3.1%	-13.3%	0.5%	2.1%	-4.0%
	Net Zero	GCAM	-1.4%	-4.2%	0.2%	0.7%	-1.6%
		MESSAGE	-1.6%	-5.1%	0.3%	0.8%	-1.9%
		REMIND	-1.1%	-2.8%	0.2%	0.5%	-1.2%

Note: The table reports CPL estimates for selected sector–country combinations and for the overall Developed Europe equity benchmark across alternative modelling assumptions. The highlighted line corresponds to the parameter specifications used in the results section.

5. Conclusion

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5. Conclusion

This paper develops a parsimonious framework to quantify the long-horizon valuation impacts of physical climate risk on listed firms and diversified equity portfolios. By re-estimating country-specific temperature–damage functions and embedding these macroeconomic losses within a discounted-cash-flow structure augmented with sector-level discount rates and vulnerability adjustments, the analysis provides a consistent mapping from NGFS scenarios to firm- and portfolio-level CPL. The empirical application reveals three central findings: physical risk is highly heterogeneous across European countries, sectoral characteristics strongly amplify this heterogeneity, and diversified regional portfolios exhibit non-trivial losses under plausible climate trajectories. These results underscore both the materiality of physical climate risks and the value of forward-looking scenario-based metrics for investors and regulators.

This paper provides a top-down basis for quantifying long-horizon valuation impacts of physical climate risk on European equities but is not without caveats. Macroeconomic damages are transmitted proportionally to firm cash flows, abstracting from firm-specific resilience or adaptation strategies. Baseline cash-flow dynamics are assumed to track baseline GDP growth, and firms are treated as passive recipients of macroeconomic shocks, without endogenous adaptive responses through investment, production, or supply-chain structures. Discount rates are held constant across scenarios, thereby excluding potential changes in risk premia as perceptions of physical climate risk evolve. While these simplifications enhance tractability, they also point to avenues for refinement.

A promising direction for future research is to integrate physical and transition risks within a unified valuation framework, allowing for interactions between mitigation pathways, adaptation responses, and macro-financial dynamics. Another important extension concerns the probabilistic weighting of climate scenarios, in the vein of Venmans and Carr (2024) and Rebonato and Melin (2025), enabling the construction of unconditional, distribution-aware measures of long-term climate risk. Such developments, alongside state-dependent discounting, would further enhance the relevance of CPL metrics for strategic asset allocation, regulatory stress testing, and climate-aware portfolio design.

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Appendix

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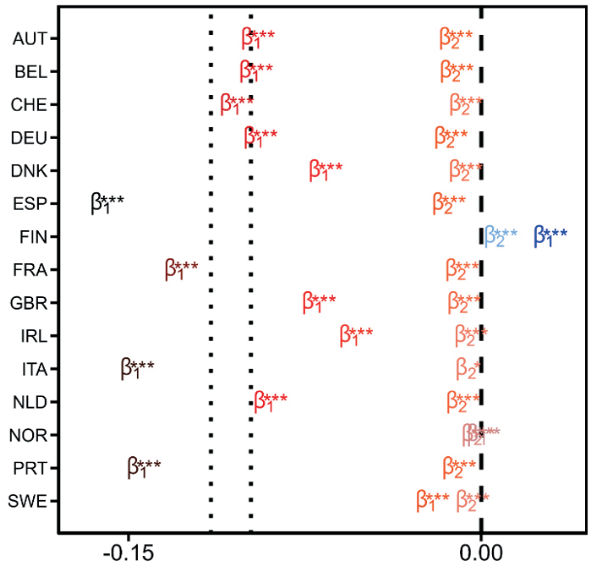
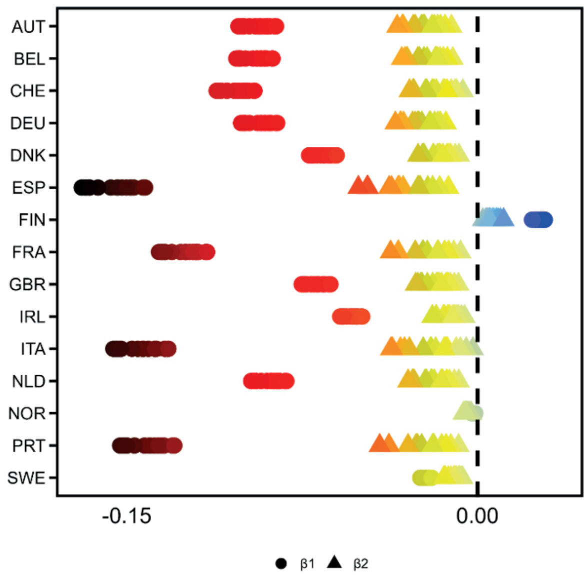
Appendix

Exhibit 10: Damage function estimated parameters by country



*Notes: Country names are denoted by their corresponding ISO3 code. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Vertical dotted lines denote the three country groups (from right-to-left: low risk, medium risk and high risk) identified in Exhibit 8.*

Exhibit 11: Sensitivity of damage function parameters to scenario and models



Notes: Coefficients plotted above 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).

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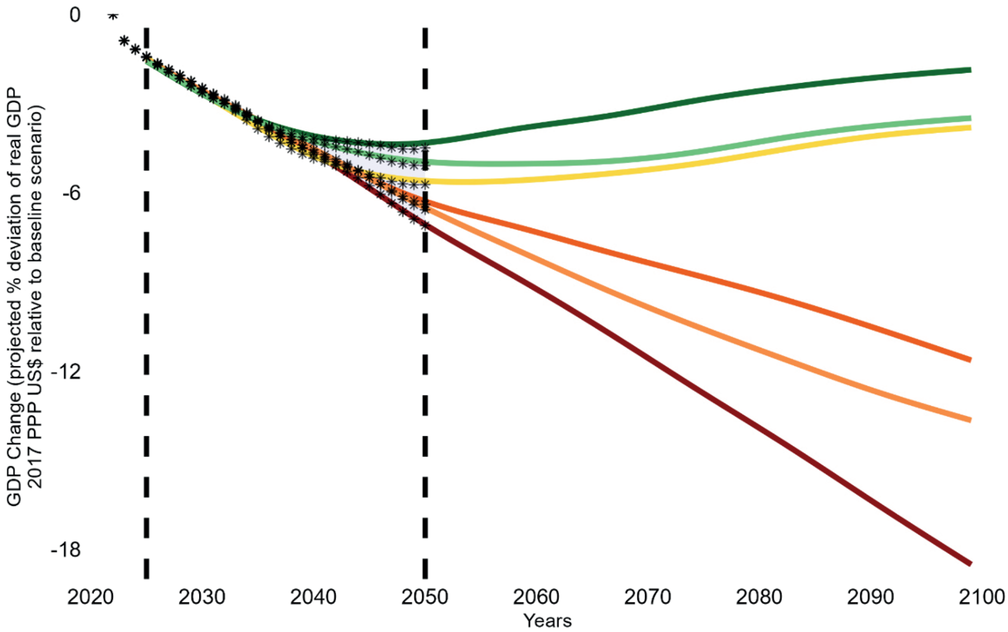
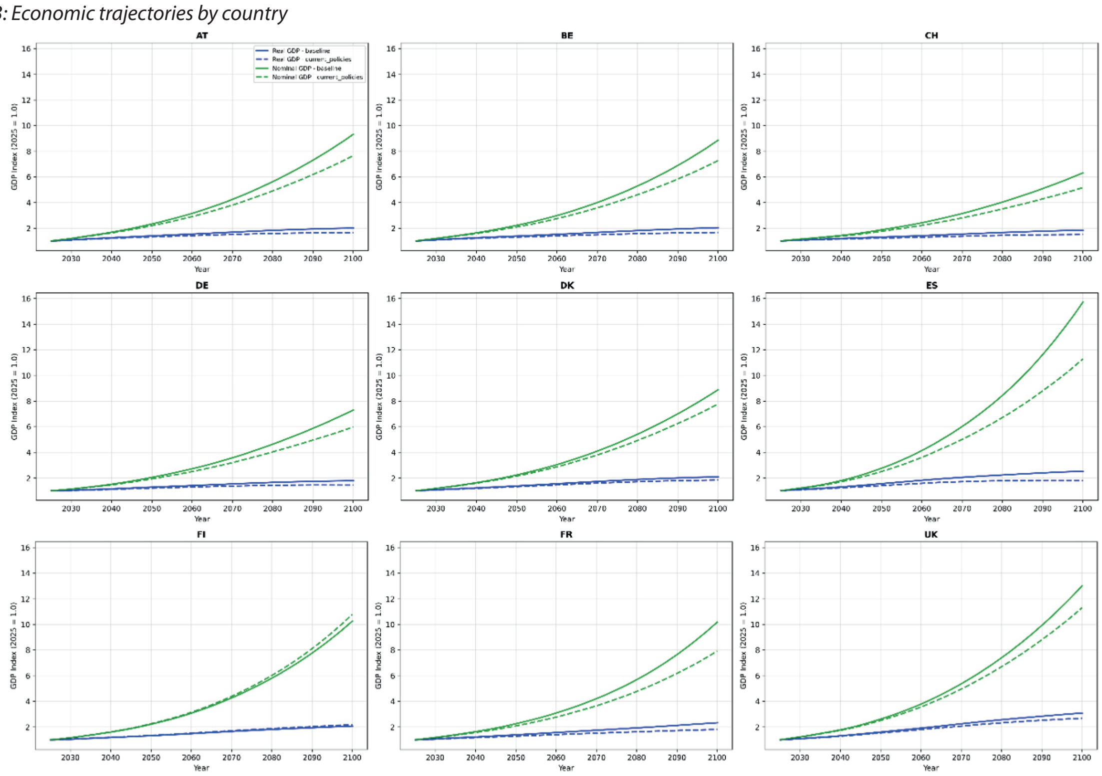
Appendix

Exhibit 12: European-level GDP deviations across NGFS scenarios



Notes: The analysis employs the GCAM 6.0 NGFS IAM. Europe-level GDP deviations are calculated as the average across the sampled countries. NiGEM-projected annual GDP changes from physical impacts for 2022–2050 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 this robustness check only, GDP deviations are normalized to 2022 instead of the usual 2025 reference year.

Exhibit 13: Economic trajectories by country



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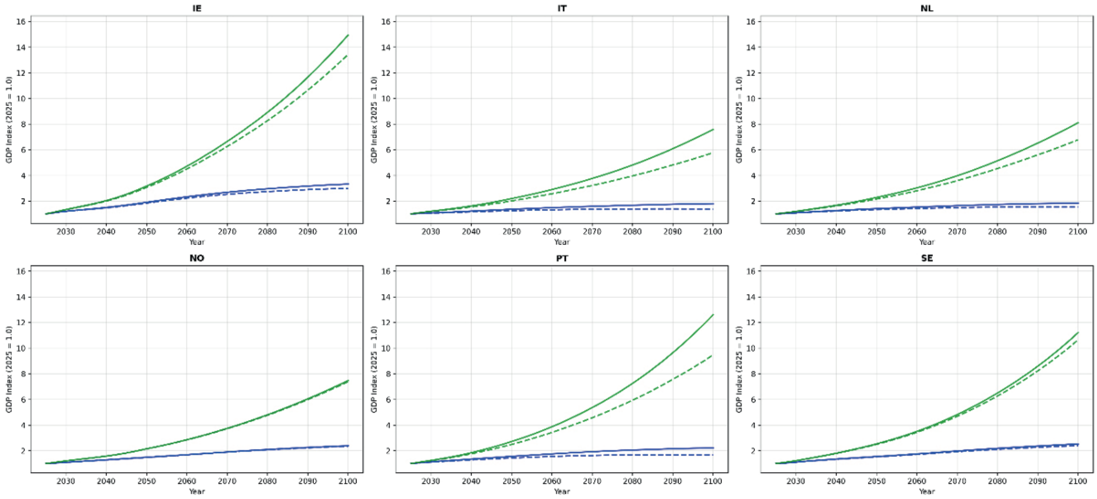
Appendix



Notes: The figure displays projected GDP trajectories for each country in the sample, comparing baseline and Current Policies (CP) paths under the GCAM integrated assessment model. Real and nominal GDP indices are shown, each normalized to 1.0 in 2025. Solid lines correspond to baseline projections, while dashed lines depict Current Policies outcomes. Green curves represent nominal GDP, and blue curves represent real GDP.

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About Scientific Portfolio

Scientific Portfolio is the latest commercial venture incubated within the research ecosystem of EDHEC Business School (EDHEC), one of the world's leading business schools.

Scientific Portfolio has assembled a team with a broad range of expertise and backgrounds, including financial engineering, computer science, sustainable and climate finance, and institutional portfolio and risk management. It proudly carries EDHEC's impactful academic heritage and aspires to provide investors with the technology they need to independently analyse and construct equity portfolios from both a financial and extra-financial perspective.

To achieve this, it offers investors three sources of value through its portfolio analysis & construction platform:

- Helping investors to analyse their equity portfolios, identify actionable insights and enhance portfolios with allocation functionalities. Indeed, Scientific Portfolio likes to promote portfolio analysis as a means to the concrete goal of building portfolios that are both more efficient and better aligned with their investment objectives.
- Providing investors with an integrated framework where financial and extra-financial (ESG) considerations are jointly captured in analysis and portfolio construction. The ability to incorporate ESG-related insights in the portfolio allocation process is now a common requirement among many investors.
- Giving investors access to a Knowledge Centre catering to all types of learners and providing guidance through the portfolio analysis and construction process. This aligns with Scientific Portfolio's commitment to remaining connected with its academic roots and bridging the gap between investors and academia.

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