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A Scientific Portfolio Publication

Physical Climate Risk in the United States Equity Market: Quantifying State–Sector Heterogeneity

March 2026

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Abstract

This paper develops a parsimonious, scenario-analysis framework to quantify physical climate loss for US listed firms and equity portfolios. Physical climate loss is defined as the valuation loss arising from climate-induced physical damage, obtained by scaling future cash flows with country-to-State disaggregated economic deviations projected 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 500 large U.S. firms and an U.S. equity benchmark reveals strong cross-state and cross-sector heterogeneity in exposure to physical climate risk, as well as a portfolio-level loss of roughly – 4.0% 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 U.S. states, from about –48.6% in Florida to modest gains in Alaska.

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

• The U.S. equity benchmark exhibits a CPL of approximately –4.0%, with results robust to model specification but sensitive to the scenario–horizon combination.

Keywords: Physical Climate Risk, Equity Market.

1. Introduction

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 (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 United States, 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 physical and transition risks may 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); however, the rule has been stayed following legal challenges, and in 2025 the SEC ceased defending it in court, leaving its implementation uncertain[1] Within the banking sector, U.S. prudential regulators have explored climate risk primarily through supervisory exercises rather than binding stress tests. Although explicitly not designed as capital adequacy stress tests, the exercises demonstrated that physical climate risks can affect credit risk (Federal Reserve, 2024).

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) synthesized 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. For instance, Acharya et al. (2022) exploited regional variations in exposure to heat stress and empirically found that exposure to heat stress is associated with higher yield spreads for corporate bonds. Most recently, Kempa (2026) compiled a global dataset of nearly 86,000 syndicated bank loans merged with country level climate vulnerability statistics proxying firm level exposure and found that higher physical climate risk in a firm's host country is associated with higher borrowing costs. This effect is particularly pronounced for long-maturity loans or firms in financial distress, and is accompanied by adjustments in loan size, collateral requirements, or fees to manage the borrower's exposure to physical risk. Finally, Smith (2025)[2] used indicators from Bloomberg and Riskthinking.AI and found that firms with higher physical

1 - Reuters. 2025. "U.S. SEC Votes to Stop Defending Climate Disclosure Rules." March 27, 2025.
2 - https://www.bloomberg.com/professional/insights/sustainable-finance/does-physical-climate-risk-carry-a-financing-premium/

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risk exposure (+10 percentage points in asset damage rate) face a +22bps premium in their weighted average cost of capital. This suggests that markets appear to be already pricing *some* of the physical risk, but the exact extent is uncertain.

Forward-looking methodologies therefore play a central role to complement these analyses. Campiglio et al. (2023) classify forward-looking 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 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 aggregate GDP deviations are subsequently disaggregated across U.S. states according to each state's relative economic weight and exposure to physical climate risks, thereby relying on sub-national projection outputs from the EDHEC Climate-Induced Regional Macro-Impacts Projector (EDHEC-CLIRMAP) database. These are finally incorporated into a discounted-cash-flow model in which firm-level cash flows grow with state 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 the 500 largest U.S. publicly listed firms and the corresponding U.S. equity benchmark. First, physical climate risk displays pronounced heterogeneity across states. Under the NGFS current policy scenario, projected deviations of nominal GDP in 2100 range from approximately –48.6% in Florida to modest gains in Alaska, with systematically larger output losses in southern states. 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

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further amplifies this dispersion. Third, at the portfolio level, the U.S. equity benchmark exhibits a weighted physical climate loss of approximately –4.0%. 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.

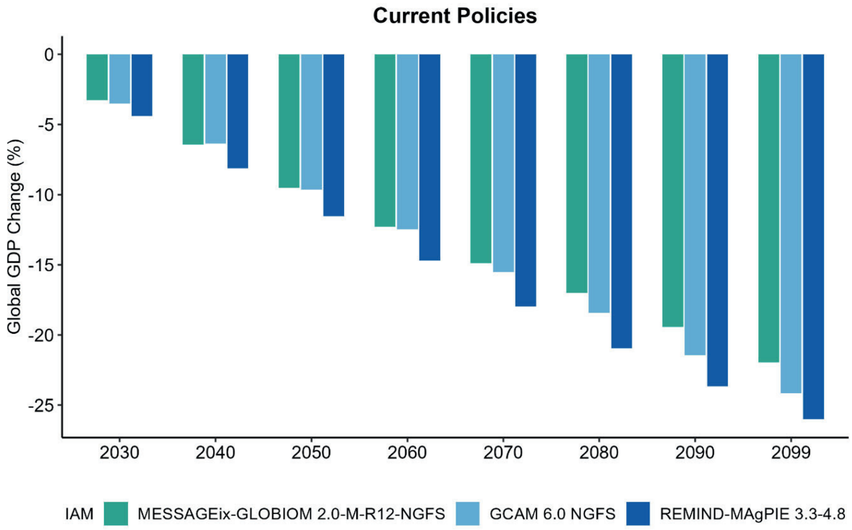
The remainder of the paper is structured as follows. Section 2 outlines the development of U.S. state-specific damage functions and the accompanying valuation model. Section 3 presents the empirical findings. Section 4 reports robustness checks and sensitivity analyses. Section 5 concludes and discusses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

2. Model and Data

2. Model and Data

The proposed framework quantifies a climate physical loss (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 (DCF) model. All macroeconomic inputs and physical risk parameters are calibrated to the scenario set published by the Network for Greening the Financial System (NGFS), thereby ensuring methodological alignment with prevailing supervisory and regulatory practices. Exhibit 0 provides a global overview of the *cascading* economic losses likely to unfold on the horizon, consistent with the literature on this topic.

Exhibit 0: Global physical risk-induced GDP change (%) by epoch and NGFS-IAM under the Current Policies scenario, compared with a baseline scenario in which no physical risks occur (i.e., no-climate-change impacts counterfactual). Source: our elaboration based on country-level projected damage estimates for 47 major economies, extrapolated from Bouchet and Schneider (2025)—originally limited to the Eurozone—to the full NGFS-NiGEM sample.



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- and state-level economic output, which in turn proportionally scales the expected cash flows of firms domiciled in the affected regions. 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 climate physical loss.

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

3 - 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).

4 - The climate-economics literature has gradually clarified the relationships between anthropogenic emissions, rising temperatures, and macroeconomic impacts. Until about fifteen years ago, estimates of climate-related damages (i.e., denoted Ω, measured as the percentage deviation of GDP relative to a reference scenario or baseline) were based largely on global macroeconomic assessments, providing limited 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 integrated assessment models (IAMs) and served as a reference for many subsequent models. Nordhaus' enumerative approach (1991) laid the methodological foundation for DICE and related IAMs, although models such as FUND and PAGE were developed independently with different structures. Early IAM approaches, as well as Weitzman (2010), were criticized for relying on damage functions that had limited empirical or theoretical support, which posed challenges for empirical validation (Pindyck, 2013). Burke et al. (2015) represents one of the first empirical approaches using panel econometric methods to link annual per capita GDP series to plausibly exogenous variations in average temperature.

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Regional economic losses from temperature anomalies

The global non-linear effect of temperature on economic production[3] has been empirically confirmed in Burke et al. (2015) and Newell et al. (2021), providing evidence for an inverted U-shaped relationship[4], whereby temperatures exceeding a turning-point generate amplifying reductions in per capita GDP. We adapt this literature to estimate climate damages at the U.S. state level using a two-phase approach that ensures consistency between national and sub-national projections.

We first estimate a quadratic damage function for the United States linking temperature anomalies to GDP damages arising from both chronic and acute[5] climate physical risk impacts,

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

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

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

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.

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 state related to the current state (not to a baseline scenario), as provided by a different database of macroeconomic damages: EDHEC-CLIRMAP (EDHEC-CLimate-Induced Regional MAcroimpacts Projector)[6]. This procedure is done to ensure maximum consistency between the NGFS U.S. country damages and the regional damage.

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

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

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

$$\theta_t = \frac{\Delta y_{US,t}}{\sum_s w_s . L_s}$$

Where $w_s = GDP_s / \sum_s GDP_s$ represents state s's share of total U.S. GDP (20-year centered moving average). This approach ensures perfect aggregation ($\sum_s w_s \, \Delta y_{s,t} = \Delta y_{US,t}$) 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.

5 - This element is further detailed in 2.2.

6 - This is a proprietary EDHEC research building on Schneider (2025). Details on the quantitative methodology underlying this module are provided in §2.2 *Data and model calibration.*

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

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

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 $s(j)$ the state 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[7]

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

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

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

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

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

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 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 normalized to the unit interval:

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

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

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

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

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- and U.S. state-level macroeconomic projections characterize both the baseline trajectory of aggregate economic activity and the deviations from this trajectory induced by temperature anomalies. Second, sector-level measures of the weighted average cost of capital (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.

2.2.1 Estimation of U.S. economic loss sensitivity to temperature anomalies

The U.S. economic sensitivity to a non-linear function of global temperature anomalies, $\beta_{1,i}^{G}$ and $\beta_{2,i}^{G}$ in equation (1), is 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 integrated assessment models (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[8]. 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[9] of 1,661 provinces in 88 countries to plausibly exogenous[10] weather fluctuations over the period 1979–2019[11] in a global panel fixed-effect (Fes) model with N and M lagged variables, whether temperature or precipitation (respectively) presented in equation (8) below,

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

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_y 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.

(2) The ISIMIP-processed CMIP6 dataset[12] provides projections of future 2 m temperature and precipitation totals from 21 distinct Global Climate Models (GCMs) simulated under the Coupled Model Intercomparison

8 - Climate projections from the Coupled Model Intercomparison Project Phase 6 (CMIP6) that have been bias-adjusted, downscaled, and harmonized within the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) framework to ensure consistency and comparability across climate-impact models.

9 - From Wenz et al. (2023)'s MCC-PIK Database of Sub-national Economic Output (DOSE).

10 - 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.

11 - 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 Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) and provided on a 0.5°×0.5° daily resolution grid.

12 - See https://data.isimip.org/ (repository) and https://gmd.copernicus.org/articles/12/3055/2019/ (academic reference).

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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 realizations 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[13], is Δy_(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, $\boldsymbol{\beta^G_{1,i}}$ and $\boldsymbol{\beta^G_{2,i}}$, are obtained by estimating a pooled specification that interacts temperature anomalies with time-invariant country indicators:

$$\Delta y_{i,t} = \sum_i [\beta^G_{1,i} C_i \, \Delta T_t + \beta^G_{2,i} C_i \, (\Delta T_t)^2] + \varepsilon_{i,t},$$

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 $\boldsymbol{\beta^G_{1,i}}$ and $\boldsymbol{\beta^G_{2,i}}$ 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, $\boldsymbol{\beta^G_{1,i}}$ and $\boldsymbol{\beta^G_{2,i}}$ 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 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).

13 - https://www.ngfs.net/ngfs-scenarios-portal/data-resources

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Given that this scenario-analysis framework is explicitly designed to quantify physical climate losses for U.S.-listed firms and equity portfolios, we extract the U.S.-specific vector of $\beta_{1,i}^{G}$ and $\beta_{2,i}^{G}$ from the ensemble obtained from Eq. (1). Exhibit 10 in Appendix empirically confirms the stability of estimated coefficients across NGFS scenario x IAM combinations.

2.2.2 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[14]. 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).

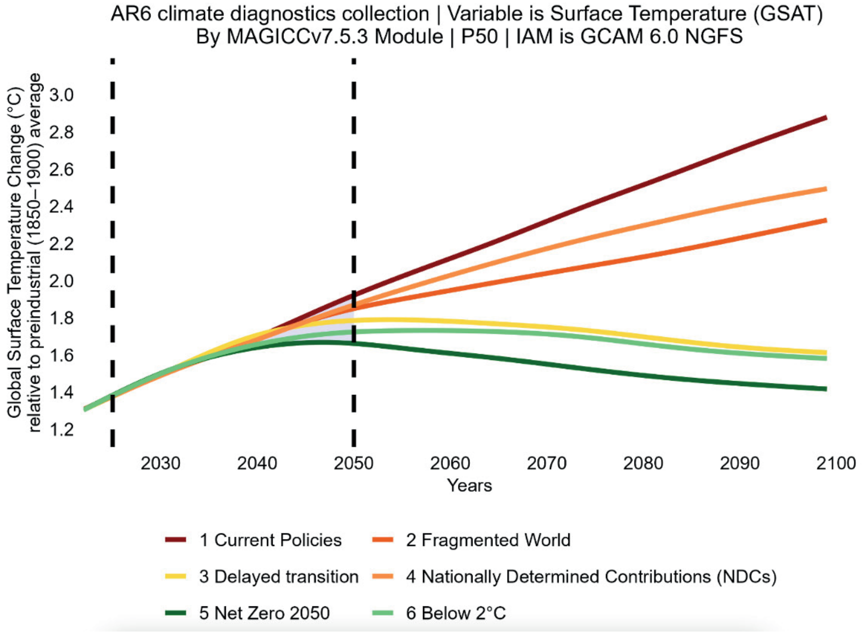
Country-level deviations from this baseline under physical climate risk are generated by applying the estimated damage coefficients to an exogenous global mean temperature (GMT) trajectory. The main scenario considered in the empirical analysis presented in the Results section is the NGFS “Current Policies”, because it is the most likely to occur (Rebonato et al, 2025). The associated GMT series, produced by the GCAM integrated assessment model, is interpolated to annual frequency and recentered 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 minimized. Exhibit 1a 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, $\mathrm{G}_{\mathrm{i,t}}^{\mathrm{phys}}$ and $\mathrm{G}_{\mathrm{i,t}}^{\mathrm{base}}$, which in turn determine the evolution of firms’ expected cash flows.

14 - SSP2 represents a “middle-of-the-road” socioeconomic pathway characterized by moderate population and productivity growth, limited inequality, and an absence of major structural shocks.

2. Model and Data

Exhibit 1a: Global mean temperature scenario trajectories
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. This pattern of narrow range is no longer observed beyond the year 2060.



2.2.3 U.S. state-level GDP damages

A limitation of NGFS Phase-V is the absence of intra-country breakdown of GDP deviations relative to the baseline scenario. This is particularly relevant for the U.S., where states vary widely in both economic activity (considering size and sectoral composition) and climate regimes, meaning that a country-level metric would obscure important regional differences. To account for such heterogeneity, national GDP deviations are downscaled to the state level by combining each state's share of U.S. GDP with its climate loss factor. States' shares of U.S. GDP are sourced from the Bureau of Economic Analysis[15]. The climate loss factor, which captures the relative economic damage per state compared to the current state, is obtained from the EDHEC-CLIRMAP database[16]. We now turn to a concise overview of this module.

EDHEC-CLIRMAP is a web-hosted interactive tool developed by the EDHEC Climate Institute. It offers a user-friendly platform for scientists, experts, and professional investors to visualize how climate change–induced shifts in average temperature are projected to affect GRP under various warming scenarios.

EDHEC-CLIRMAP methodology is documented in (i) 'EDHEC-CLIRMAP: The Macroeconomic and Econometric Background'[17], (ii) 'EDHEC-CLIRMAP: A High-Level View'[18] and (iii) 'EDHEC-CLIRMAP: The How-To Guide' , but can be traced in greater detail to (iv) Schneider (2025). This paper provides a six-step theoretical and empirical basis for making more spatially localized projections of physical climate risk-driven economic damages.

15 - Available at: https://www.bea.gov/data/gdp/gdp-state.
16 - Available at: https://climateinstitute.edhec.edu/data-visualisations/edhec-clirmap
17 - https://climateinstitute.edhec.edu/sites/default/files/2025-07/ECI_Macroeco_Econometric_Background_EDHEC-CLIRMAP.pdf
18 - https://climateinstitute.edhec.edu/sites/default/files/2025-07/ECI_High_Level_Note_EDHEC-CLIRMAP.pdf
19 - https://climateinstitute.edhec.edu/sites/default/files/2025-08/ECI_The_How_To_Guide_CLIRMAP_0.pdf

2. Model and Data

In sum, a theoretical framework first models how highly non-linear, short-run changes in productivity (occurring across clusters of micro-units[20]) scale up to shape macro-GDP responses over longer horizons. Second, a climate-GDP historical dataset is assembled, covering consistent geographic, income and climate zones. The third stage quantifies global per capita GRP responses to historical fluctuations in the set of physical risk components. Fourth, a projection dataset is elaborated, by calculating climate change-driven shifts in a given physical risk factor from NASA Earth Exchange Global Daily Downscaled Projections outputs simulated under the CMIP6 exercise. Stage five applies the 'Delta' method for projected damages, consisting of 'forcing' these Delta into our global GRP model calibrated prior using historical data (usually named response or transfer functions), obtaining fractional changes. Resulting damages are finally decomposed along spatial (regions) and temporal (future years or epochs) vectors, as well as climate scenarios and Global Climate Model (GCM) ensembles.

More specifically, EDHEC-CLIRMAP relies on an unbalanced panel covering the last five decades, drawing on Penn World Tables version 10.01 (166 countries)[21] and the MCC-PIK DOSE (1,661 administrative provinces at the first sub-national level) to quantify weather-driven responses of annual per capita GDP at both the country and administrative province levels. Using a top-down climate econometric approach and panel specification similar to what is commonly used in the climate-economics literature (Burke et al., 2015; Kotz et al., 2024; Bilal and Känzig, 2024), the model attributes output responses to plausibly exogenous year-to-year temperature and precipitation fluctuations (i.e., the major propagation channels of physical risk) while accounting for adaptation margins (which manifest over time in response to anticipated long-term shift in climate normals by economic agents) (Dell et al., 2014). Following McIntosh and Schlenker (2006), the fixed-effects specification isolates most of the time-series and cross-sectional variations in ambient climate measurements by exploiting the higher spatial resolution of the global dataset of subnational economic outputs. Climate variables are derived from 3-hourly temperature and precipitation fields at 0.25-degree resolution from the Global Land Data Assimilation System (GLDAS)[22] and matched to the temporal frequency and spatial resolution of end-point regional GDP realizations. NASA's GLDAS grid-cell coordinates are intersected with the different subnational administrative region identifiers[23] in which they fall. Grid-cell-level exposures are aggregated to regions using gridded population density records[24] as weights.

Estimated climate-GRP response functions, modeled as non-linear functions of temperature and precipitation (the two main propagation channels of climate change), are then combined with an ensemble of NEX-GDDP CMIP6 Global Climate Model (GCM) simulations[25] extrapolated to 3,672 sub-national regions responsible for 95% of global economic production. Climate change-driven changes in per capita output are ultimately projected under moderate (SSP2–RCP4.5) and high (SSP5–RCP8.5) warming scenarios and across GCM realizations.

20 - Consider a representative macroeconomy partitioned into sectors, under the simplifying assumption that all production units within a given sector exhibit homogeneous responses to climatic (e.g., temperature) shocks. Production in each industry takes place across multiple spatial locations within countries, each representing a large cluster of such units. The stylized sectoral production function builds on Deryugina and Hsiang (2014), with capital and labor exhibiting factor-specific productivities that depend on the contemporaneous physical risk component (e.g., temperature) experienced at a given location and point in time. For more details, see Schneider (2025).
21 - Available at: https://www.nber.org/research/data/penn-world-tables
22 - Available at: https://ldas.gsfc.nasa.gov/gldas
23 - Available at: https://atlas.co/data-sources/global-administrative-areas/
24 - Available at: https://www.earthdata.nasa.gov/data/projects/gpw
25 - Available at: https://www.nccs.nasa.gov/services/data-collections/land-based-products/nex-gddp-cmip6

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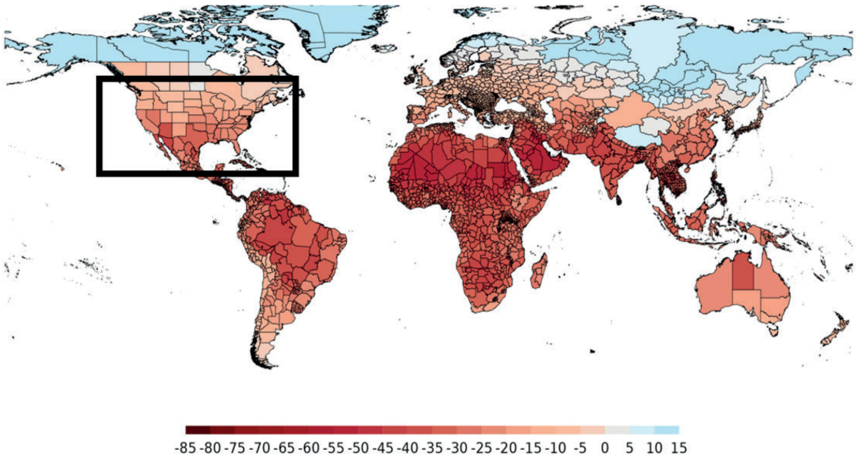
Exhibit 1b: Spatially distributed region-level projected damages (%) to per capita GDP, 2099.
Figure shows the region-distributed estimates from multi-model medians of 15 'likely' CMIP6 GCMs, epoch 2099 relative to constant historical 1985-2004 temperature means, according to a synthetic intermediate mid-point scenario between SSP5-8.5 vigorous & SSP2-4.5 moderate warmings. The black rectangle indicates the global region under explicit focus in this study. Source: Schneider (2025).



Resulting projected damages (shown in Exhibit 1b), distributed across time (i.e., future 20-year centered moving average periods spanning 2030–2099) and geographies (i.e., administrative regions subset to the 50 U.S. States), form the basis of the climate loss factor. This factor captures the relative economic damage per U.S. state compared to the current period 'without climate change' (i.e., defined as constant historical 1985-2004 temperature means), according to the selected ACCESS-ESM1-5 GCM simulated under SSP2-RCP4.5[26] moderate warming scenario.

National U.S. GDP deviations, derived from combining the outputs from Sections 2.2.1 with 2.2.2, are allocated across U.S. states based on each state's climate loss factor calculated above, and its respective share in the total U.S. GDP. This enables the calculation of nominal GDP growth factors under the baseline and physical-risk scenarios (e.g., NGFS Current Policies scenario, GCAM model) for each U.S. State as shown in Eq. (2). In the valuation stage of the methodology (Eq. 3-5), firm-level cash flows are ultimately scaled by these State-level growth factors.

2.2.4 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 weighted average cost of capital (WACC), which provide industry-level values for different regions, including United States. 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.

2.2.5 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

26 - This denotes the Australian Community Climate and Earth System Simulator (ACCESS) extended with land and ocean carbon cycle components, thereby forming an Earth System Model (ESM). For a more exhaustive review of the idiosyncratic characteristics of this GCM, see Ziehn et al. (2020). Note that ACCESS-ESM1-5 is classified a 'likely' GCM according to Hausfather et al. (2022), indicating that its representation of cloud feedbacks is *not* associated with higher-than-consensus global surface temperature response to doubled atmospheric CO2 concentrations (i.e., the equilibrium climate sensitivity) and global warming after 70 years of a 1% per annum increase in CO2 (i.e., the transient climate response).

2. Model and Data

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.

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	5.5%
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%
Health Care	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 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 Kölbel et al. (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)*

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3. Results

3. Results

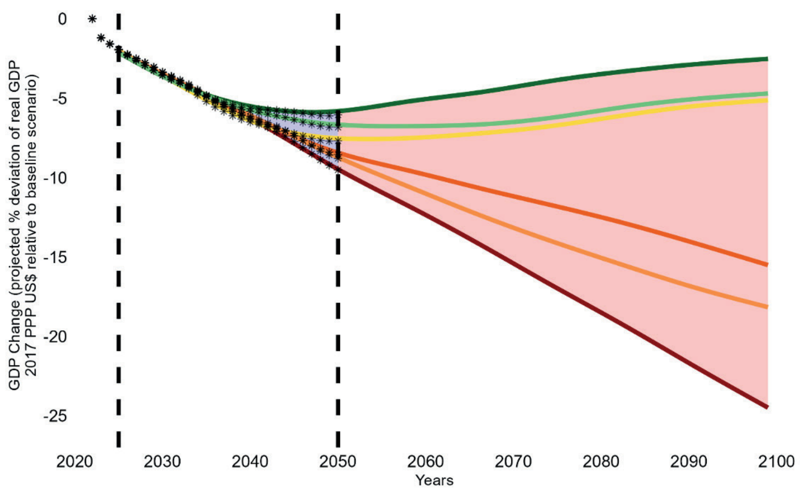
The empirical analysis focuses on the 500 largest publicly listed U.S. firms and is structured in three steps. First, it examines heterogeneity across U.S. states in estimated climate-risk sensitivities. Second, it assesses how sector-specific discount rates and sector-level exposure to physical hazards contribute to cross-sectional dispersion in outcomes. Finally, it evaluates the implications for a representative U.S. equity portfolio, illustrating how aggregate exposure to physical climate risks translates into portfolio-level valuation effects.

3.1 U.S.State-Level Economic Sensitivity to Climate Physical Risks

Exhibit 3a shows U.S.-level GDP deviations across NGFS scenarios. At 2050, neither scenario nor model selection significantly alters outcomes, whereas at 2100 scenario choice dominates, making the projection horizon a determinant factor as well. This pattern can be attributed to the widening inter-scenario range of GDP deviations observed post-2050, which can be ultimately traced back to structural differences in global temperature change trajectories from MAGICC (Exhibit 1a).

Most importantly, these country-level trajectories hide an exceptionally wide *umbrella* of state-specific damage trajectories. Standard country by year GDP changes, as typically supplied by climate scenario providers, tend to overlook this regional heterogeneity. It is therefore of interest to consider the much broader state-level distributions of mid- and end-century U.S. damages resulting from physical climate risks. This is now what we turn to.

Exhibit 3a: U.S.-level GDP deviations across NGFS scenarios.
The figure uses the GCAM 6.0 NGFS IAM. U.S.-level GDP deviations as calculated from 2.2.1 and 2.2.2. 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 (represented by the blue shaded area), prior to extrapolation through 2100 (represented by the red shaded area). For this robustness check only, GDP deviations are normalized to 2022 instead of the usual 2025 reference year.

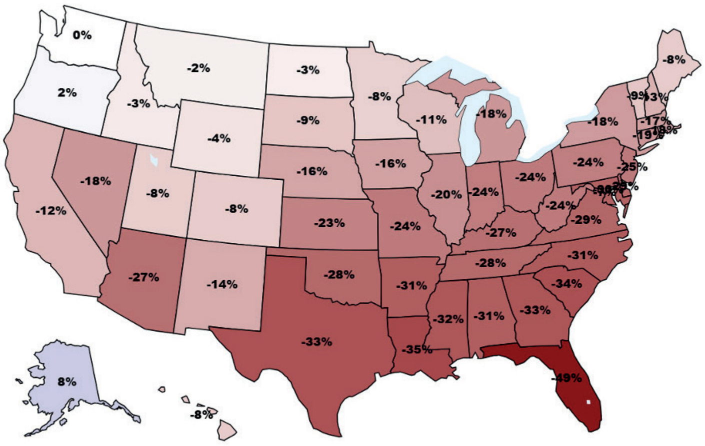


Across the 50 U.S. states, projected long-term economic outcomes exhibit substantial heterogeneity, ranging from an estimated gain of around 8% for Alaska to a loss of approximately 49% for Florida.

3. Results

These differences are strongly correlated with latitude: southern states face markedly larger economic losses, while only two states - Alaska and Oregon - are projected to experience relative gains from cooler climatic conditions (Exhibit 3b).

Exhibit 3b: Projected nominal GDP loss by 2100 under current policies for U.S. states
The figure reports, for each U.S. 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.



3.2 Sector-specific discounting and vulnerability effects

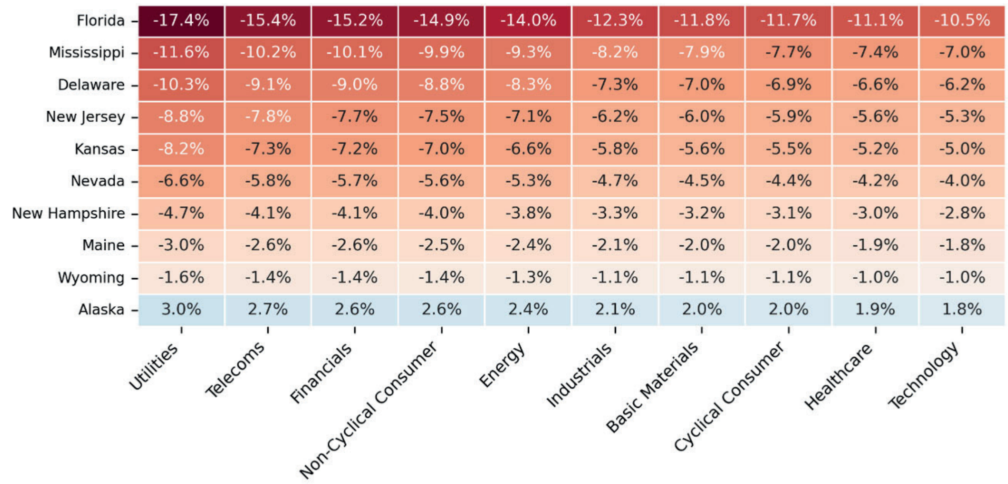
Building on the U.S. state-level sensitivity to physical climate risks, the model incorporates two sector-specific adjustments. The first relates to heterogeneity in the weighted average cost of capital (Exhibit 2). Because projected physical damage generally rises over time, sectors characterized by 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).

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 climate physical loss (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.

Exhibit 4: Effect of sector-specific discount rate only on climate physical loss

3. Results

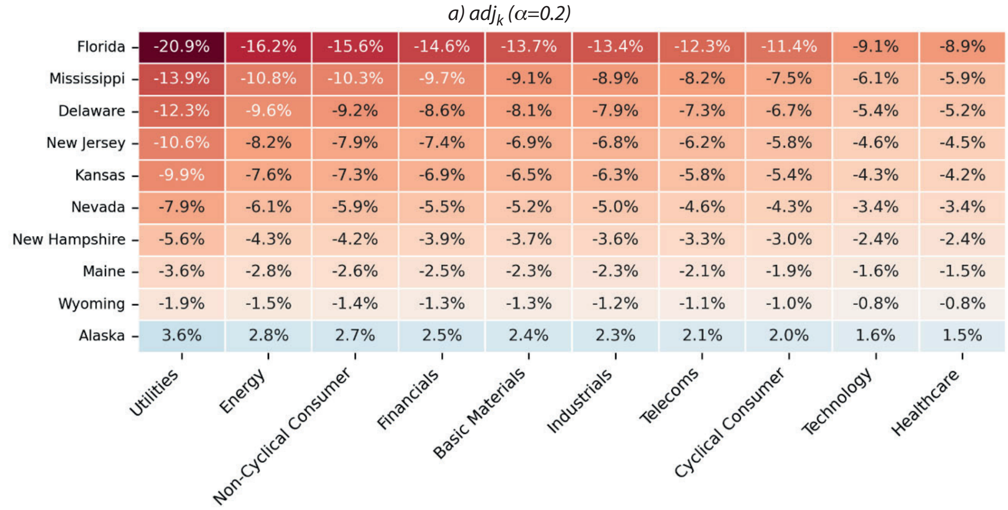
The heatmap displays the climate physical loss (CPL) for a selection of 10 U.S. state–sector pairs after incorporating sector-specific discount rates. Sectors with low weighted average cost of capital tend to exhibit higher CPL as they are more sensitive to the long-term impact of climate change on their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



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 (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 climate physical losses declines substantially (Exhibit 5).

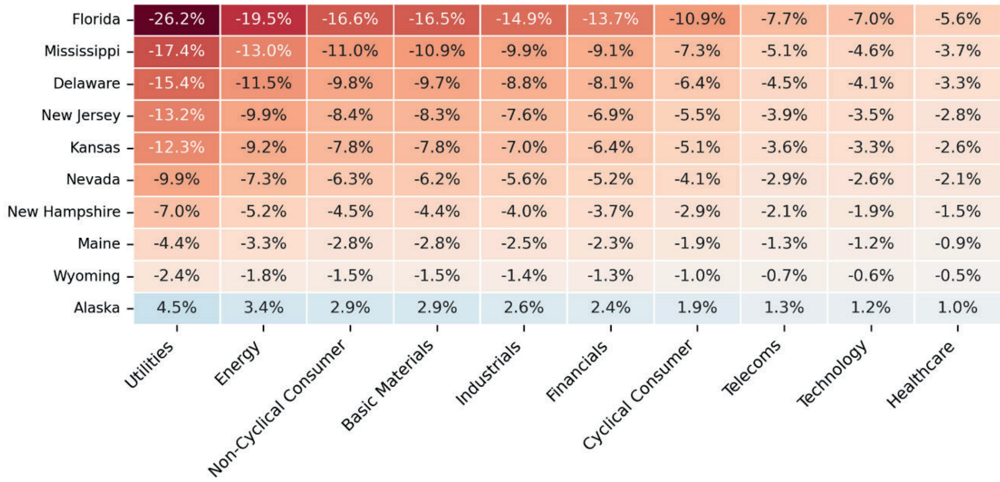
Exhibit 5: Combined effect of sector discount rate and vulnerability on climate physical loss
The heatmaps display the climate physical loss (CPL) for a selection of U.S. state–sector pairs after incorporating both sector-specific discount rates and sectoral vulnerability to physical climate risks. For the vulnerability adjustment, two values of the scaling parameter a (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.

a) adj_k (α=0.2)



3. Results

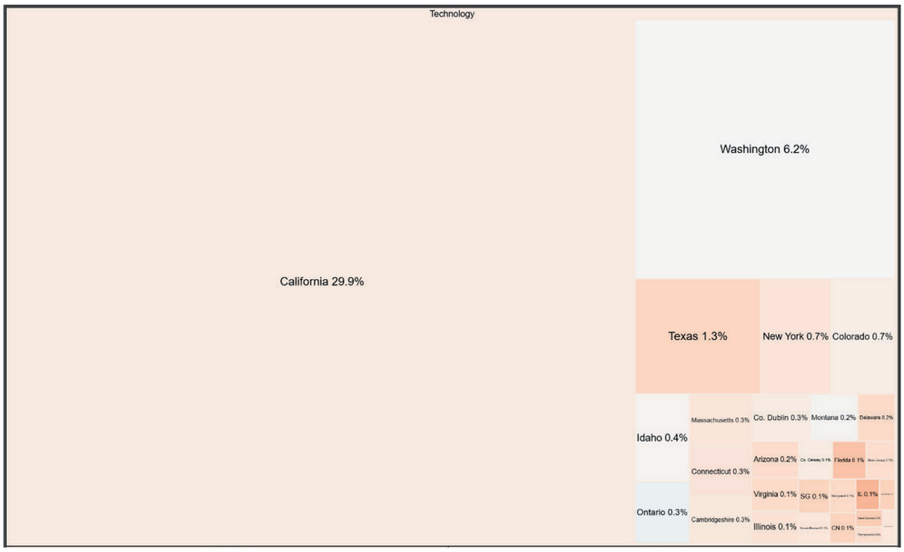
b) adj_k (α=0.5)



3.3 Application to a U.S. equity benchmark

Within the sample of U.S. states and sectors, the estimated climate physical loss (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 U.S. cap-weighted equity benchmark, the weighted CPL amounts to −4.0%. Exhibit 6 highlights the distribution of state-sector allocation jointly with the corresponding vulnerability levels.

Exhibit 6: Sector and state allocation of the U.S. equity benchmark
The figure displays the joint state–sector composition of the U.S. cap-weighted equity benchmark alongside each segment's estimated climate physical loss (CPL). Rectangle size reflects the benchmark weight of each state–sector, while color intensity represents the corresponding CPL value (from lower losses in light tones to higher losses in darker tones).



3. Results

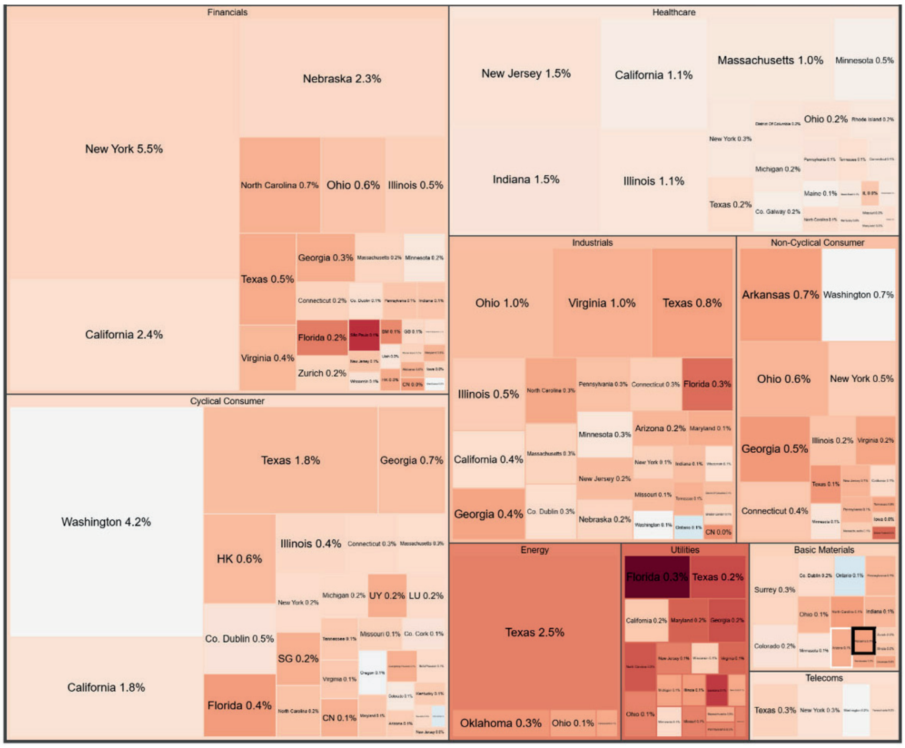


Exhibit 7 illustrates how alternative state- and sector-weightings would influence this result. Under an equal-weight allocation across all U.S. states (50) and sectors (10, the CPL would be –5.33%. Replacing equal sector weights with the benchmark's sector weights improves the CPL to –4.00%, implying a favourable sector-allocation effect. In contrast, applying the benchmark's state weights while maintaining equal sector weights yields to a more limited CPL of –4.41%. This decomposition shows that the benchmark's sector allocation highly mitigates climate exposure, and that this effect is exacerbated by the state-allocation effect, driven by overweight positions in states with lower physical-risk exposure.

Exhibit 7: Climate physical loss of the U.S. equity benchmark
The table reports the weighted climate physical loss (CPL) under alternative allocations. "Equal" allocates identical weights to each of the 50 U.S. states (or 10 sectors) in the sample, while "Portfolio" applies the weights of the U.S. equity benchmark to the corresponding states or sectors.

Allocation	State allocation	Sector allocation	Weighted CPL
Equal State & Equal Sector (Baseline)	Equal	Equal	-5.33%
Equal State & Portfolio Sector	Equal	Portfolio	-4.00%
Portfolio State & Equal Sector	Portfolio	Equal	-4.41%
U.S. equity benchmark	**Portfolio**	**Portfolio**	**-3.97%**

4. Sensitivity Analysis

4. Sensitivity Analysis

The structural nature of the framework implies sensitivity to several assumptions, particularly those related to the underlying input data. This section evaluates the sensitivity of the climate physical loss results for the U.S. equity benchmark to the choice of horizon, scenario, and integrated assessment 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 climate physical loss (CPL), whether computed at the state-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 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, which can be ultimately traced back to structural differences in global temperature trajectories (Exhibit 1a).

Exhibit 9: Climate physical loss sensitivity to horizon, scenario and model
The table reports climate physical loss (CPL) estimates for selected sector–state combinations and for the overall U.S. equity benchmark across alternative modelling assumptions. The highlighted line corresponds to the parameter specifications used in the results section.

Horizon	Scenario	Integrated Assessment Model	(Florida) Healthcare	(Florida) Utilities	(Alaska) Healthcare	(Alaska) Utilities	U.S. Portfolio
2050	Current Policies	GCAM	-3.0%	-10.3%	0.5%	1.8%	-1.9%
		MESSAGE	-3.0%	-10.5%	0.5%	1.8%	-1.9%
		REMIND	-3.6%	-12.7%	0.6%	2.2%	-2.3%
	Fragmented World	GCAM	-2.8%	-9.8%	0.5%	1.7%	-1.8%
		MESSAGE	-3.1%	-10.7%	0.5%	1.9%	-2.0%
		REMIND	-3.4%	-11.5%	0.6%	2.0%	-2.1%
	Net Zero	GCAM	-2.3%	-7.8%	0.4%	1.4%	-1.5%
		MESSAGE	-2.6%	-8.6%	0.4%	1.5%	-1.6%
		REMIND	-2.1%	-6.9%	0.4%	1.2%	-1.3%
2100	Current Policies	**GCAM**	**-5.6%**	**-26.2%**	**1.0%**	**4.5%**	**-4.0%**
		MESSAGE	-5.5%	-25.2%	0.9%	4.4%	-3.9%
		REMIND	-6.5%	-29.7%	1.1%	5.1%	-4.6%
	Fragmented World	GCAM	-4.5%	-19.2%	0.8%	3.3%	-3.1%
		MESSAGE	-4.7%	-19.0%	0.8%	3.3%	-3.2%
		REMIND	-5.1%	-21.5%	0.9%	3.7%	-3.5%
	Net Zero	GCAM	-2.4%	-7.4%	0.4%	1.3%	-1.5%
		MESSAGE	-2.8%	-8.8%	0.5%	1.5%	-1.7%
		REMIND	-1.9%	-5.1%	0.3%	0.9%	-1.1%

5. Conclusion

5. Conclusion

This paper provides a forward-looking assessment of physical climate risk in U.S. equity markets using a parsimonious, NGFS-aligned valuation framework. The results document substantial heterogeneity in long-run climate exposure across U.S. states, with projected GDP losses by 2100 ranging from small gains in high-latitude states such as Alaska to losses approaching 50% in highly exposed southern states such as Florida. On average, U.S. states exhibit stronger macroeconomic sensitivity to physical climate risks than Developed Europe countries, reflecting both climatic gradients and the spatial concentration of acute and chronic hazards.

However, this higher underlying exposure does not translate mechanically into larger portfolio-level losses. Once state- and sector-level damages are aggregated using equity benchmark weights, the U.S. cap-weighted equity benchmark displays a weighted physical climate loss of around - 4.0% under a current policies scenario. This figure is slightly lower than the - 4.7% estimated for the Developed Europe equity benchmark using the same methodological framework (Bouchet & Schneider, 2025).

The difference is primarily driven by the sector effect: the sectoral structure of the U.S. benchmark offsets the higher average physical risk embedded at the macro level. In particular, the U.S. benchmark is relatively more exposed to high-WACC, lower-sensitivity sectors and less concentrated in the most physically vulnerable regions than a simple equal-weight allocation would imply. By contrast, the Developed Europe benchmark remains more heavily weighted toward countries with elevated long-run physical risk exposure, which dominates the mitigating effect of its sector allocation. These results highlight that physical climate risk is not only a function of regional exposure but also of portfolio construction.

Overall, the comparison between the United States and Europe underscores a key implication for investors: higher average climate exposure at the geographic level does not necessarily imply higher portfolio-level risk. Sector and regional allocations play a first-order role in shaping effective exposure, reinforcing the need to assess physical climate risk jointly through macroeconomic sensitivity and benchmark composition when informing strategic asset allocation.

References

References

- Acharya, V. V., Johnson, T., Sundaresan, S., & Tomunen, T. (2022). Is physical climate risk priced? Evidence from regional variation in exposure to heat stress (Working Paper No. 30445). Cambridge, MA: National Bureau of Economic Research.
- Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, 32(4), 33-52.
- Auffhammer, M., Baylis, P., & Hausman, C. H. (2017). Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. Proceedings of the National Academy of Sciences, 114(8), 1886-1891.
- Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., & Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, 7(4), 283-288.
- Bilal, A., & Känzig, D. R. (2024). The macroeconomic impact of climate change: Global vs. local temperature (Working Paper No. 32450). National Bureau of Economic Research.
- Bouchet, V., & Schneider, N. (2025). Physical Climate Risk in the European Equity Market: Quantifying Country–Sector Heterogeneity. Scientific Portfolio Working Paper.
- Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. American *Economic Journal: Economic Policy*, 8(3), 106-140.
- Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. Nature, 527(7577), 235-239.
- Campiglio, E., Daumas, L., Monnin, P., & von Jagow, A. (2023). Climate-related risks in financial assets. *Journal of Economic Surveys*, 37(3), 950-992.
- Dell, M., Jones, B. F., & Olken, B. A. (2014). What do we learn from the weather? The new climate-economy literature. J*ournal of Economic literature*, 52(3), 740-798.
- Deryugina, T., & Hsiang, S. M. (2014). Does the environment still matter? Daily temperature and income in the United States (Working Paper No. 20750). National Bureau of Economic Research.
- Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). 'Climate value at risk'of global financial assets. *Nature Climate Change*, 6(7), 676-679.
- Federal Reserve. (2024). Pilot Climate Scenario Analysis Exercise: Executive Summary and Results. Washington, DC: Board of Governors of the Federal Reserve System.
- Hain, L. I., Kölbel, J. F., & Leippold, M. (2022). Let's get physical: Comparing metrics of physical climate risk. *Finance Research Letters*, 46, 102406.
- Hausfather, Z., Marvel, K., Schmidt, G. A., Nielsen-Gammon, J. W., & Zelinka, M. (2022). Climate simulations: Recognize the 'hot model' problem. *Nature*, 605(7908), 26–29.
- Kalkuhl, M., & Wenz, L. (2020). The impact of climate conditions on economic production. Evidence from a global panel of regions. *Journal of Environmental Economics and Management*, 103, 102360.
- Kempa, K. (2026). Physical climate risk and the pricing of bank loans. *Journal of Environmental Economics and Management*, 103280.
- Mandel, A., Battiston, S., & Monasterolo, I. (2025). Mapping global financial risks under climate change. *Nature Climate Change*, 15(3), 329-334.
- McIntosh, C. T., & Schlenker, W. (2006). Identifying non-linearities in fixed effects models (Working Paper). UC San Diego.
- Newell, R. G., Prest, B. C., & Sexton, S. E. (2021). The GDP-temperature relationship: implications for climate change damages. *Journal of Environmental Economics and Management*, 108, 102445.
- Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *The economic journal*, 101(407), 920-937.

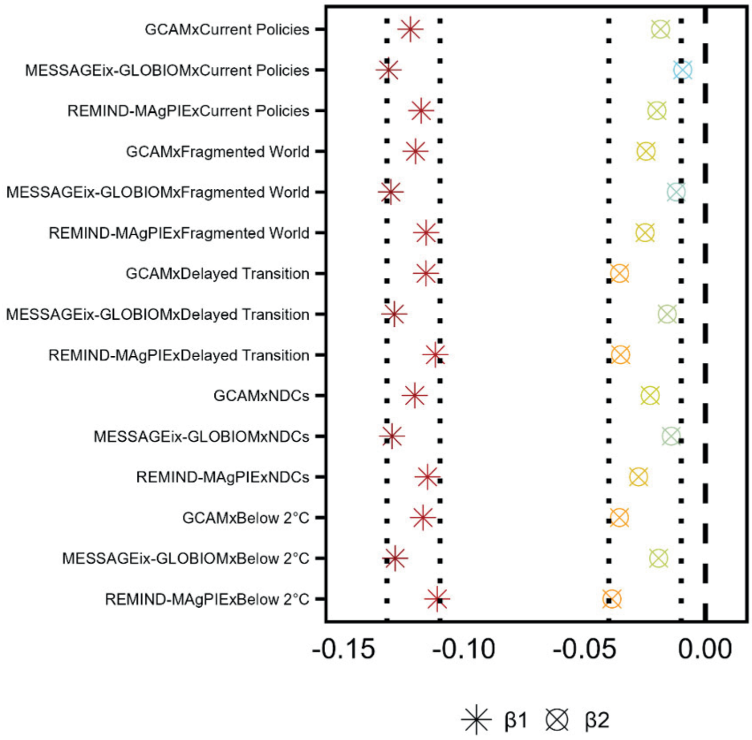
References

• Pindyck, R. S. (2013). Climate change policy: what do the models tell us?. *Journal of Economic Literature*, 51(3), 860-872.
• Pretis, F. (2021). Exogeneity in climate econometrics. *Energy Economics*, 96, 105122.
• Rebonato, R., & Melin, L. (2025). Climate scenarios with probabilities via maximum entropy and indirect elicitation. Available at SSRN 5128228.
• Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. Proceedings of the National Academy of sciences, 106(37), 15594-15598.
• Schneider, N. (2025). The Global Geography of Long-Term Projected Macroeconomic Damages from Chronic Physical Risk and the Aggregation Problem. SSRN Working Paper N*5630697.
• Securities and Exchange Commission (SEC). (2024). The Enhancement and Standardization of Climate-Related Disclosures for Investors. Final Rule. Washington, DC.
• Venmans, F., & Carr, B. (2024). Literature-informed likelihoods of future emissions and temperatures. *Climate Risk Management*, 44, 100605.
• Weitzman, M. L. (2010). What Is The" Damages Function" For Global Warming—And What Difference Might It Make?. *Climate Change Economics*, 1(01), 57-69.
• Wenz, L., Carr, R. D., Kögel, N., Kotz, M., & Kalkuhl, M. (2023). DOSE–Global data set of reported sub-national economic output. *Scientific Data*, 10(1), 425.
• Ziehn, T., Chamberlain, M. A., Law, R. M., Lenton, A., Bodman, R. W., Dix, M., … Srbinovsky, J. (2020). The Australian Earth System Model: ACCESS-ESM1.5. *Journal of Southern Hemisphere Earth Systems Science*, 70(1), 193–214.

Appendix

Appendix

E xhibit 0: Sensitivity of U.S. damage function parameters to NGFS scenarios and IAM models
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 main NGFS Phase-V scenarios. Vertical dotes lines show the narrow coefficients bandwidth of $\beta^{c}_{1,US}$ *and* $\beta^{c}_{2,US}$,



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