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From Transition to Physical Risk: Rethinking Portfolio Management

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Abstract

Over the past fifteen years, responsible investment has evolved, shifting from broad ESG scores to more granular climate risk management. Transition risk has dominated, with portfolio decarbonization anchored in standardized carbon intensity metrics and, more recently, complemented by measures of green intensity. Frameworks such as comprehensive integrated and core-satellite approaches now give investors effective tools to integrate transition risks into portfolio construction. In contrast, physical climate risk remains underdeveloped. Rising extreme weather events, chronic temperature increases, and ecosystem disruptions are already affecting asset values and supply chains. However, there is no standardized equivalent to carbon or green intensity for benchmarking.

This paper argues that physical climate risk must now receive the same attention as transition risk. Unlike transition risk, physical climate risk lacks clear anchor metrics. This methodological gap explains why portfolio optimization that incorporates physical risk is still in its infancy. We review transition and physical risk modeling and discuss approaches for constructing physical risk scores. We also examine how to integrate these scores into portfolio optimization and strategic asset allocation. Our analysis shows that achieving significant reductions in both exposure and vulnerability to physical climate risk is extremely challenging. Moreover, the high shadow price associated with these mitigation policies suggests substantial implementation costs and trade-offs. Overall, we conclude that incorporating physical climate risk into portfolio management is considerably more complex than managing transition risk.

Keywords: Climate risk, transition risk, physical risk, hazard, exposure, vulnerability, asset management, portfolio optimization, strategic asset allocation, tracking error risk, shadow pricing.

JEL classification: C61, G11, Q54.

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1 Introduction

The landscape of responsible investment and sustainable finance has undergone a profound transformation over the past fifteen years. What started as a relatively straightforward integration of environmental, social, and governance (ESG) scores into asset allocation decisions has evolved into a more sophisticated approach to managing climate-related financial risks (Roncalli, 2026). Initially, investors relied on composite ESG ratings as broad indicators of corporate sustainability performance, while seeking to preserve diversification benefits (Cesarone *et al.*, 2025). However, as the field matured, practitioners recognized some limitations of such aggregated measures and moved toward greater granularity. They began to disaggregate scores into their constituent pillars, focusing in particular on environmental metrics that could signal material financial risks. The focus on climate transition risk has emerged as a defining feature of this evolution. Carbon intensity metrics became standard tools in portfolio construction and optimization, enabling investors to measure and manage their exposure to the financial implications of decarbonization (Le Guenedal and Roncalli, 2022). This approach became more refined over time, incorporating forward-looking indicators such as carbon momentum, temperature alignment ratings, and synthetic transition scores that attempted to capture the multidimensional nature of companies' preparedness for a low-carbon economy (Le Guenedal *et al.*, 2022). These innovations reflected a growing consensus that the transition away from fossil fuels represented a fundamental shift in the global economy that would create winners and losers across sectors and geographies.

However, the investment landscape has shifted dramatically in recent years. In certain jurisdictions, an ESG backlash has gained momentum, challenging the principles and practices of sustainable finance. At the same time, political support for ambitious climate transition policies has weakened in several major economies, creating uncertainty about the pace and direction of decarbonization efforts. Most concerning, however, is the growing body of evidence indicating that the transition to a low-carbon economy is still well off track compared to the pathways required by net-zero scenarios. The gap between climate commitments and climate action continues to widen. Against this sobering backdrop, a new reality has asserted itself with undeniable force. Climate physical risks are no longer distant or hypothetical, but present and material. Extreme weather events, chronic temperature increases, water scarcity, and ecosystem disruption are occurring with increasing frequency and severity, directly affecting asset values, supply chains, and business operations[1]. The economic consequences of hurricanes, floods, droughts, and wildfires make it clear that physical climate risk is a critical dimension of portfolio risk that can no longer be overlooked or treated as secondary. This paper argues that physical climate risk must now be given the same level of analytical rigor and practical integration in portfolio management as transition risk has been over the past decade. Just as the investment community has developed sophisticated metrics, models, and optimization techniques to manage transition risk, it must now build an equivalent toolkit for assessing and managing physical risk. This shift does not imply abandoning transition risk considerations, but rather reflects the recognition that a comprehensive approach to climate-related financial risk must address both dimensions with equal seriousness and sophistication.

[1] In July 2024, Porsche faced a striking example of physical climate risk when severe flooding disrupted operations at a European aluminium supplier in Switzerland. This resulted in shortages of specialised aluminium alloys critical to all of Porsche's vehicle lines. As a result, the company was forced to lower its revenue guidance for 2024, reducing its projected sales from €40–42 billion to €39–40 billion, and its expected operating profit margin from 15–17% to 14–15%. Production delays were anticipated to last several weeks. The market reacted swiftly, with Porsche's market capitalisation falling by an estimated €2 billion. This incident highlights how physical climate shocks can have a knock-on effect through supply chains, resulting in tangible financial losses and challenging the resilience of manufacturing-intensive sectors.

In the case of transition risk, two main approaches have emerged for portfolio management: the integrated approach (Barahhou *et al.*, 2022) and the core-satellite approach (Ben Slimane *et al.*, 2023). Both approaches use carbon intensity as the anchor of climate transition metrics. Climate transition portfolios are therefore closely related to portfolio decarbonization, but have additional requirements. First, the decarbonization of portfolios must be endogenous. They should contribute to the decarbonization of the economy rather than merely reshuffling carbon exposure within financial markets. Second, transition finance must be accounted for. This implies that the greenness or green intensity of a portfolio is also a central component of any climate transition investment strategy. These two dimensions — carbon intensity and green intensity — form the core of transition-related investment (Roncalli, 2025). In practice, the carbon dimension has typically dominated, because carbon intensity provides a standardized and widely accepted measure of portfolio exposure. However, in contexts such as climate solutions and net-zero investing, the green dimension plays a more prominent role. For example, the primary objective of a portfolio of green bonds is to maximize green intensity. The same logic applies to satellite allocations within a core-satellite framework. A key reason for the asymmetry between carbon and green metrics is methodological. Carbon intensity has benefited from nearly two decades of standardization, largely thanks to the GHG Protocol, which established accounting rules for Scope 1, 2, and 3 emissions. Although imperfect, these metrics are now well-normalized and relatively trusted. This explains why they have become the backbone of transition portfolio management and net-zero investing methodologies. In contrast, the definition and measurement of green intensity are far less straightforward because they depend on the taxonomy of sustainable activities. As a result, combining carbon and green dimensions into composite climate transition scores is an ongoing development. Nevertheless, investors now have the necessary tools to integrate transition risk into portfolio optimization and asset allocation.

The picture is more complex for physical risk[2]. While a growing — albeit slow — academic literature has examined the financial implications of physical climate hazards, much of this work remains outside the domain of portfolio construction. Early contributions focused on how firms interpret and respond to physical risks, emphasizing vulnerability assessment and adaptation strategies (Gasbarro and Pinkse, 2016). In a pioneering effort to quantify system-wide financial impacts, Dietz *et al.* (2016) introduced the concept of climate value-at-risk, providing a physical risk counterpart to the climate stress-testing framework for transition risk developed by Battiston *et al.* (2017). However, this early approach relied heavily on damage functions derived from integrated assessment models, thereby inheriting their structural assumptions and limitations. More recent empirical studies provide mixed evidence regarding the pricing of physical risks in financial markets. Albanese *et al.* (2025) found that equity markets are increasingly sensitive to both acute and chronic physical risks. By contrast, Acharya *et al.* (2022) documented market sensitivity to heat stress in both bond and equity markets, but found little evidence that other physical risks are priced[3]. Similarly, Pankratz *et al.* (2023) confirmed that extreme temperatures and heat waves adversely impact corporate performance. These divergent results may be partly explained by differences

[2]Here, we discuss the contrasting development trajectories of transition risk versus physical risk from the perspective of the financial industry. From a scientific standpoint, research on physical risk predates research on transition risk, and the scientific corpus on physical risk is vastly larger than that addressing transition risk (Roncalli, 2026, Chapters 8 and 12). For example, IPCC reports devote significantly more content to physical risk than to transition risk, particularly in earlier assessment reports and those prepared by Working Group I (The Physical Science Basis). Thus, while the analysis of transition risk lags behind that of physical risk from a climate science perspective, the opposite is true in finance. Integrating physical risk into financial analysis is less advanced than integrating transition risk — with the notable exception of the insurance industry, which has been at the forefront of physical risk modeling for decades.

[3]See also Cisagara (2024) about the impact of temperature risk on stock returns.

in the time horizons across studies[4]. Nevertheless, a relative consensus has emerged in recent years. A growing body of evidence indicates that physical risk affects the pricing of debt instruments, including loans, mortgages, municipal and corporate bonds (Javadi and Masum, 2021; Nguyen *et al.*, 2022; Correa *et al.*, 2023; Calabrese *et al.*, 2024), and more generally the credit risk (Ginglinger and Moreau, 2023; Azzone *et al.*, 2026). There is now enough literature on this topic that several surveys have been published recently (Zhou *et al.*, 2023; De Bandt *et al.*, 2025). By contrast, the integration of physical climate risk into asset management and portfolio construction remains largely unexplored in the academic literature[5]. To our knowledge, only three studies directly address this topic. The first extends the Merton model to incorporate physical risk (Milic *et al.*, 2025). The second is a Master's thesis conducted at SEB Asset Management measuring physical risk at the fund level (Bäckman, 2025). The third integrates physical risk into a climate Black-Litterman model to incorporate fund managers' views into portfolio allocation (Bhaugeerutty, 2026).

Unlike transition risk, there is no clear equivalent to carbon intensity or green intensity that can serve as a simple anchor metric. This absence explains why asset allocation methods that explicitly incorporate physical risk are still in their infancy, whereas investors already have access to numerous transition-focused benchmarks and methods across both equity and bond markets. In fact, there are several challenges. The first is related to measurement. Current approaches primarily rely on composite scoring systems, which are imperfect indicators of underlying hazards. Improving the granularity, transparency, and robustness of physical risk metrics, as well as shifting toward more direct data-driven measures, remains a central priority[6]. Moreover, downscaling these climate data to company- and asset-level resolution remains highly problematic. The second challenge lies in aggregation. Physical risk is multidimensional by nature, encompassing acute and chronic components as well as a wide range of hazards, such as floods, hurricanes, droughts, and heat stress. Developing coherent methods to compare and combine these heterogeneous sources of risk into meaningful portfolio indicators is far from straightforward. A third difficulty relates to vulnerability. Much of the existing literature has focused on measuring exposure to physical hazards, but considerably less attention has been given to assessing vulnerability, that is the ability of firms, regions, or sectors to withstand and adapt to these shocks. However, vulnerability is a critical determinant of realized financial losses and, therefore, of investment risk. Progress in measuring damage functions, vulnerability curves and loss rates — again at the company- and asset-level resolution — will be essential in the coming years. Finally, beyond measurement and aggregation issues, there is the broader task of developing physical risk portfolio construction frameworks that are comparable to those already established for transition risk.

This paper is structured as follows. Section Two illustrates the differences between transition risk and physical risk. Specifically, we define the two main components of physical risk: acute and chronic risks. We also present the general framework used to measure physical risk. Section Three shows how to integrate physical risk into portfolio management. In particular, we focus on two exercises: equity portfolio optimization and strategic asset allocation. We estimate the maximum achievable reduction in climate physical risk, distinguish between exposure risk and vulnerability risk, and compute the shadow price of implementing physical risk constraints. Finally, Section Four concludes with closing remarks.

[4]It is traditionally assumed that transition risk impacts the short term while physical risk impacts the medium and long term (Gambhir *et al.*, 2022).

[5]We omit studies on physical risk and asset pricing which, while potentially useful for bottom-up asset picking, offer limited practical implications for top-down asset allocation.

[6]The challenges associated with physical risk data and their uncertainty are well-documented in the literature (Hain *et al.*, 2022; ESMA, 2024). In particular, concerns have been raised about the transparency of certain model-based approaches: "*[...] many providers of climate services use black box models that make overseeing the scientific rigor of their methodologies impossible*" (Condon, 2023, page 147).

2 Climate risk modeling

2.1 Transition risk

Transition risk relates to the transition to a low-carbon economy and the associated changes in regulations, technology, and consumer preferences:

> "*On the other hand, the mitigation of climate change, by means of a transition to a low-carbon economy, requires a transformation of the energy and production system at a pace and scale that implies adverse impact on a range of economic activities, but also opportunities for some other activities (high confidence). If these impacts are factored in by financial markets, they are reflected in the value of financial assets. Thus, transition risks and opportunities refers to the component of financial risk (opportunities) associated with negative (positive) adjustments in assets values resulting directly or indirectly from the low-carbon transition.*" IPCC (2022, Chapter 15, page 1581),

We generally consider four main forces that drive transition risk: changes in consumer preferences and demand; climate regulation through carbon pricing mechanisms such as carbon taxes and emission quotas; stranded assets and the valuation risk associated with these assets. Additionally, we account for financing risk because access to funding is essential to transitioning to a low-carbon economy.

2.1.1 Shifting preferences and demand

Transition risk arises not only from policy, regulatory and technological changes, but also from evolving consumer preferences (NGFS, 2022, page 10). The report by TCFD (2017) identifies potential transition risks as policy and legal risks, technological risks, as well as the market risk and reputational risks. Market risk may also emerge from changes in customer behavior that could lead to decreased demand for certain commodities, products, and services. Additionally, shifts in consumer preferences toward more sustainable options may result in reputational risk for companies that fail to adapt. Notably, there is an increasing tendency for demand to shift away from high-carbon sectors towards goods and services that are perceived as more sustainable. At the same time, investors are increasingly interested in green and sustainable funds and assets, seeking to align their portfolios with environmental objectives and mitigate exposure to sectors that could be negatively affected by the transition to a low-carbon economy. As a result, companies and financial institutions that fail to adapt to these evolving preferences may face significant financial risks, including asset devaluation and erosion of market share.

Changes in consumer demand and preferences can significantly facilitate the transition to a low-carbon economy:

> "*The indicative potential of demand-side strategies to reduce emissions of direct and indirect CO_2 and non-CO_2 GHG emissions in three end-use sectors (buildings, land transport, and food) is 40–70% globally by 2050 (high confidence).*" (IPCC, 2022, Technical Summary, page 117).

The actions with the greatest mitigation potential involve changes in individual mobility, such as switching from driving to walking cycling or using public transport. Another remarkable shift is toward vegetarian and vegan diets. However, Rizzati *et al.* (2025) show that consumer green preferences alone are insufficient to drive the transition to a low-carbon economy. Substantial emissions reductions require effective regulatory frameworks, as well as businesses internalizing these preferences in their strategies and operations.

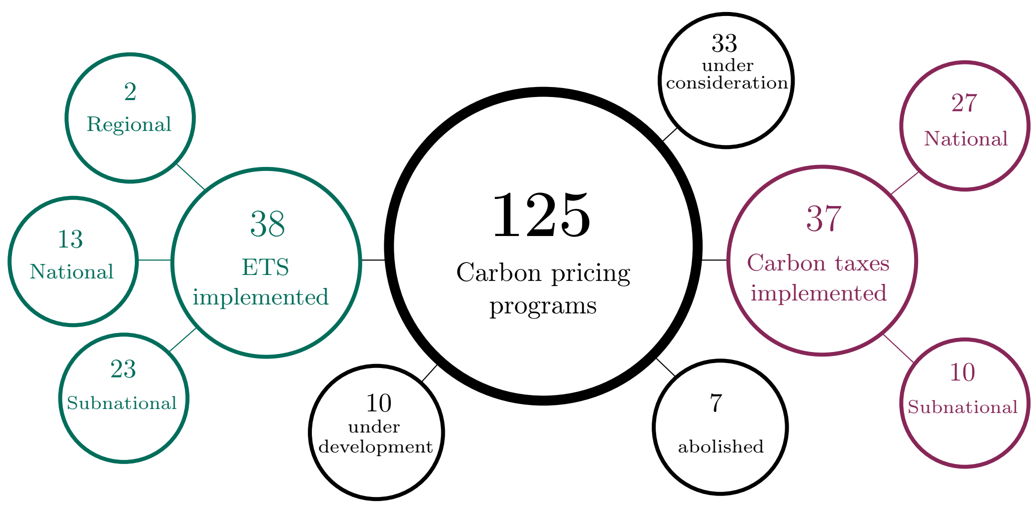
2.1.2 Carbon pricing and regulation

Carbon pricing is the main tool used in public climate policies to reduce CO_2 emissions:

> "*Carbon pricing is an instrument that captures the external costs of greenhouse gas (GHG) emissions — the costs of emissions that the public pays for, such as damage to crops, health care costs from heat waves and droughts, and loss of property from flooding and sea level rise — and ties them to their sources through a price, usually in the form of a price on the carbon dioxide emitted.*" (World Bank, 2021), `carbonpricingdashboard.worldbank.org`.

There are various carbon pricing practices. As of December 2023, there were 125 carbon pricing initiatives worldwide, though only 75 were in effect (Poupard *et al.*, 2022; Dao *et al.*, 2024). Figure 1 provides an overview of current carbon pricing mechanisms.

Figure 1: Global network of carbon pricing mechanisms as of December 2023



Source: Dao *et al.* (2024, Figure 1, page 6).

All of these mechanisms share the same goal: ensuring that the largest emitters of greenhouse gases pay higher taxes and face higher costs. This increases the cost of brown activities, resulting in market innovation. Furthermore, carbon pricing generates revenue for governments to finance the transition to a low-carbon economy. One of the most common carbon pricing mechanisms is the carbon tax, which sets a fixed price per tonne of CO_2 emitted. Typically, carbon tax rates are calculated based on the carbon content of various fuels and expressed as the cost per tonne of CO_2 emitted:

$$\boldsymbol{\mathcal{C}} = \tau \cdot \boldsymbol{\mathcal{CE}}$$

where τ is the carbon tax expressed in $\$/tCO_2$ (or tCO_2e) and $\boldsymbol{\mathcal{CE}}$ are the carbon emissions expressed in tCO_2 (or tCO_2e). For example, if the carbon tax is \$50 per tonne of CO_2 and the emission factor is 2.3 kg of CO_2 per liter of gasoline, the tax is approximately 11.5 cents per liter of gasoline:

$$\boldsymbol{\mathcal{C}} = \frac{\$50}{1\,000 \text{ kg}} \times \frac{2.3 \text{ kg}}{1 \text{ liter}} = \$0.115 \text{ per liter}$$

In this case, the cost of emissions is fixed, but the environmental impact is uncertain because issuers can choose to pay the tax without reducing emissions. Carbon tax mechanisms vary greatly from country to country and can be applied as stand-alone policies or supplements to other mechanisms. Furthermore, they can be applied at different levels of the supply chain, meaning the tax could be paid by either producers or consumers.

While carbon taxes are price-based instruments, carbon emissions can also be regulated through a quantity-based policy instrument such as an emissions trading scheme (ETS), which operates through the trading of fixed emission allowances between entities in a carbon market. An ETS functions by setting an aggregate cap on total allowable emissions across all participating entities:

$$\sum_{j \in \mathrm{ETS}} \boldsymbol{\mathcal{CE}}_j \leq \boldsymbol{\mathcal{CE}}^{+}_{\mathrm{ETS}}$$

where $j \in \mathrm{ETS}$ denotes an entity covered by the ETS, $\boldsymbol{\mathcal{CE}}_j$ is the carbon emissions of entity j, and $\boldsymbol{\mathcal{CE}}^{+}_{\mathrm{ETS}}$ is the overall emissions cap imposed by the system regulator. To operationalize this limit, a corresponding number of emission allowances (or permits) are issued or auctioned to entities. Each allowance typically grants the right to emit one tonne of $\mathrm{CO_2}$e. The distribution of allowances must also respect the cap:

$$\sum_{j \in \mathrm{ETS}} \mathcal{EA}_j \leq \boldsymbol{\mathcal{CE}}^{+}_{\mathrm{ETS}}$$

where $\mathcal{EA}_j$ denotes the emissions allowances allocated to entity j. In order to comply, each entity must surrender allowances equal to its actual emissions. There are two main types of ETS. There is a cap-and-trade system, which sets an absolute maximum limit on emissions. In this system, emission allowances are distributed and auctioned, and can subsequently be traded by market participants. The second one is a baseline-and-credit system. In this case, each entity possesses its own emissions baseline level. Entities that have successfully reduced their emissions below this level are awarded a credit, which is then traded by entities that have exceeded it. Several ETS systems operate worldwide, most notably the European Union's ETS, which was implemented in 2005 and has undergone multiple phases of adjustment to align with evolving climate targets. Unlike carbon taxes, which set the price of emissions, an ETS determines the quantity of emissions permitted while allowing the market to establish the price (Dao *et al.*, 2024; Roncalli, 2026). Figure 2 shows the global status of ETS and carbon taxes, including implemented systems, those under development, and those under consideration.

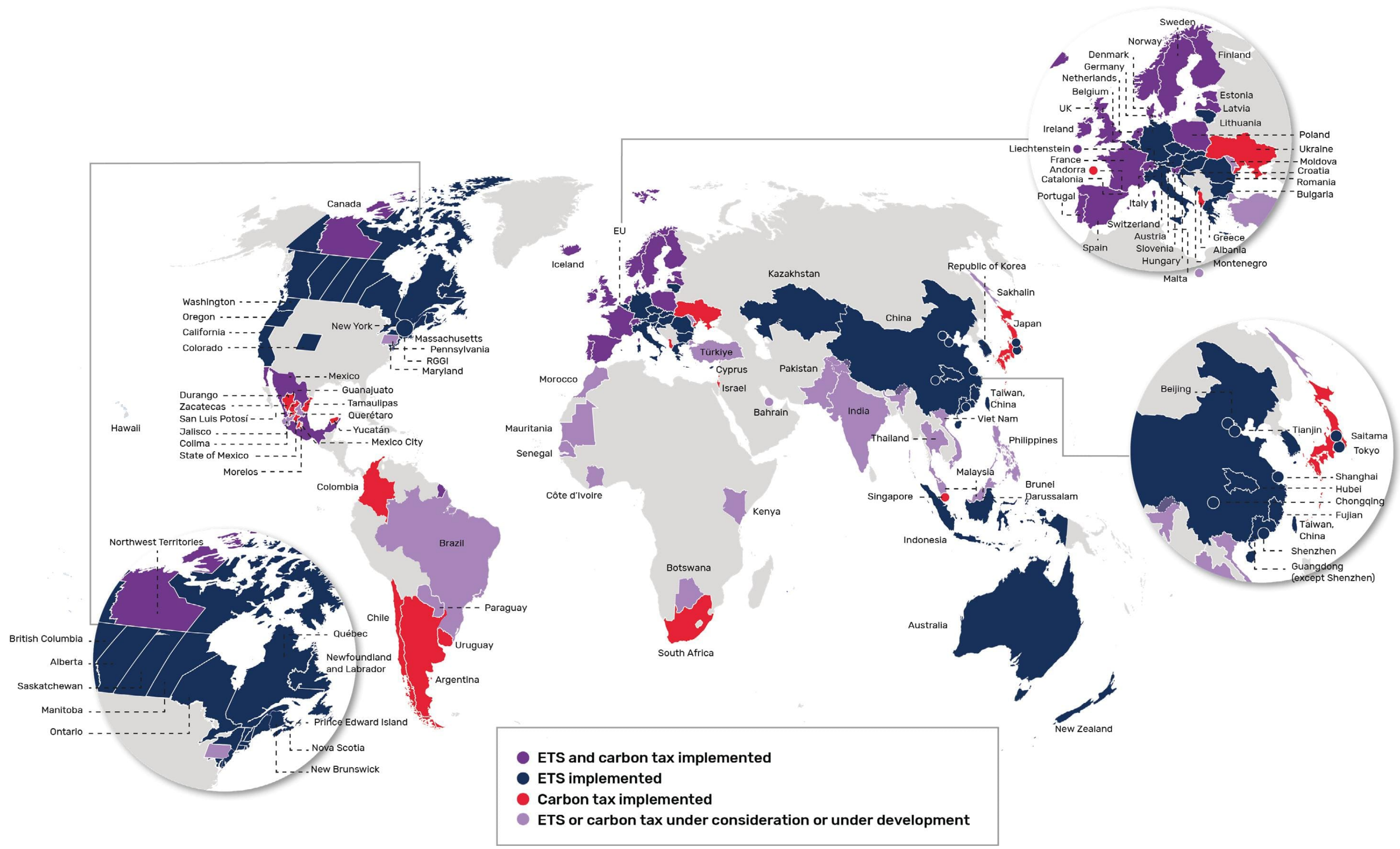
The carbon pricing methods discussed above are government-managed external mechanisms. However, internal carbon pricing methods also exist, adopted voluntarily by companies as risk management instruments to monitor transition risk and reallocate resources toward low-carbon activities. Three main internal carbon pricing methods are commonly used (Roncalli, 2026):

1. Shadow pricing assigns a hypothetical carbon price, *i.e.* an estimate of the cost that could result from future regulations, to assess the long-term environmental and financial impacts of business decisions.

2. Internal carbon fee is a kind of self-imposed carbon tax, representing the monetized value of greenhouse gas emissions generated by company operations. The tax generates revenue for the company that can be allocated to transition funds or sustainability projects.

3. Implicit carbon price represents the actual cost incurred by a company to mitigate greenhouse gas emissions. It is calculated retrospectively by considering actions taken to reduce emissions and comply with regulations.

Figure 2: Global map of ETS and carbon taxes implemented, under development, or under consideration



Source: World Bank (2025, Figure 2, page 22).

2.1.3 Stranded assets and valuation risk

The term "*stranded assets*" in the context of climate change was popularized by the Carbon Tracker Initiative through its seminal January 2011 report "*Unburnable Carbon — Are the World's Financial Markets Carrying a Carbon Bubble?*". This publication introduced the concept to financial market, arguing that meeting climate targets would render a significant portion of fossil fuel reserves *unburnable*, creating substantial stranded asset risk for investors (Carbon Tracker Initiative, 2011). Following this pioneering work, the concept spread among regulators, central banks and academics. One of the most widely accepted definition of stranded assets is the one of Ben Caldecott (Caldecott *et al.*, 2013, 2016):

> "*Stranded assets are assets that have suffered from unanticipated or premature writedowns, devaluations, or conversion to liabilities.*"

Daumas (2024) distinguishes between three categories of stranded assets: resources, capital, and paper. Stranded resources are raw materials and natural resources that cannot be exploited due to regulatory changes and new climate targets. Examples include unburned fossil fuel resources, as well as forests and land that cannot be used. Stranded capital refers to machinery, equipment, and physical infrastructure that lose market value by becoming obsolete prematurely, such as fossil fuel power plants and carbon-intensive factories. Finally, the financial repercussions of stranded resources and capital can result in stranded paper/assets, such as declines in equity value and the emergence of nonperforming loans (Roncalli, 2026). Since Caldecott *et al.* (2013), it has been demonstrated that the issue of stranded assets is not exclusive to the energy sector and its associated fossil fuels. Rather, all sectors are at risk of stranding (Chester *et al.*, 2024). The table in Roncalli (2026, pages 1013-1015) provides an overview of several sectors exposed to stranded assets and their main exposures.

The measurement of stranded assets falls into three main categories (Daumas, 2024). The first category involves non-monetary estimates of physical assets or reserves, often referred to as *Unburnable carbon* (Carbon Tracker Initiative, 2011). To meet climate targets, such as limiting global warming to 2°C, the majority of existing fossil fuel reserves would need to remain unexploited. Under this scenario, the stranded carbon is estimated to represent about 80% of total reserves (Roncalli, 2026). The literature proposes several metrics, expressed in physical units, like capacity, physical quantities and the age of capital stocks (Fisch-Romito *et al.*, 2021). However, these measures do not account for the associated economic costs. The second category focuses on monetary estimates. This approach provides financial assessments of potential accounting losses and asset write-downs resulting from the premature decommissioning of assets required to meet climate targets, as well as the future cash flow losses induced by the green transition. According to Daumas (2024), such losses can be assessed using two metrics: book loss (realized and recorded loss) and forgone revenue, which captures an opportunity cost. In monetary terms, stranded assets can thus be defined as the difference between the value of assets under a baseline scenario (*e.g.*, business-as-usual scenario) and their value under a climate stabilization scenario (*e.g.*, a 2°C pathway):

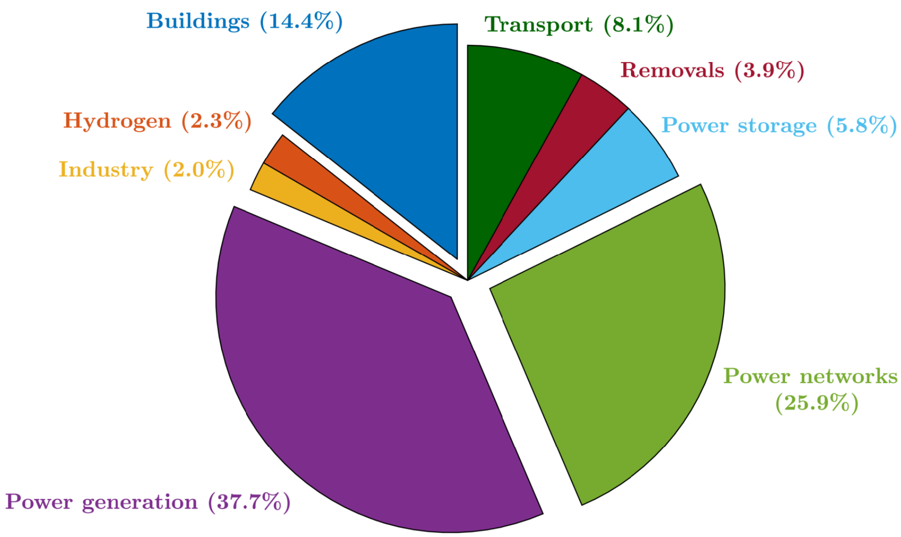
$$\mathit{Stranded}\left(t_0, T\right) = \mathcal{VA}_{\text{Baseline}}\left(t_0, T\right) - \mathcal{VA}_{\text{Climate}}\left(t_0, T\right)$$

Both of these approaches adopt a bottom-up perspective, whereas the third category relies on a top-down approach. This final category encompasses studies that estimate potential financial losses for institutions arising from transition risk, which includes losses associated with stranded assets and other factors. The evaluation of transition risk typically involves financial network analysis, climate stress testing, and scenario-based modeling (Desnos *et al.*, 2023).

2.1.4 Financing risk

As noted by Ben Slimane *et al.* (2023), transforming the entire global value chain to achieve a net-zero economy both requires and depends on substantial financial investment. According to McKinsey (2022), approximately $9.2 trillion per year will be needed, leaving a funding gap of about $3.5 trillion. The distribution of these investments is uneven across sectors, as illustrated in Figure 3. As expected, the energy sector accounts for the largest share (around 70% of total investment needs) allocated among energy production, networks, and storage. This is followed by the construction and transport sectors.

Figure 3: Net-zero capital investments



Source: Energy Transitions Commission (2023, page 9) & Ben Slimane *et al.* (2023).

According to Energy Transitions Commission (2023), the financing required for the transition to a low-carbon economy can be divided into two main categories. The first category comprises capital investments from both the private and public sectors in physical infrastructure and machinery, which are expected to yield financial returns. As stated by Energy Transitions Commission (2023), "*we estimate [these capital investments] needs to average about $3.5 trillion a year to 2050, partially offset by a $0.5 trillion per annum reduction in fossil fuel investments to leave a net figure of $3trn per annum. This compares with estimated current low-carbon investment levels of around $0.9–1.2 trillion.*" The second category involves concessional and grant-based financing, aimed at covering the costs of activities that lack sufficient economic incentives and therefore do not generate direct financial returns. These funds typically support initiatives such as reforestation projects and the accelerated closure of coal-fired power plants. Such financial flows are primarily directed toward middle- and low-income countries, and Energy Transitions Commission (2023) estimates that they may need to reach at least $300 billion per year by 2030.

Remark 1. *Another key constraint to the feasibility of the transition is the availability of critical metals and the concentration of their supply chains. Low-carbon technologies require large quantities of copper, lithium, nickel, cobalt, and rare earth elements. Constraints in refining capacity lead times could cause bottlenecks and price volatility. Therefore, scaling up recycling, diversifying upstream capacity, and investing in material-efficient designs and alternative chemistries are essential complements to financing and policy.*

2.2 Physical risk

In this section, we define the concept of physical risk, which is often misunderstood, as it is commonly associated only with extreme weather events and natural catastrophes. However, physical risk also encompasses the broader dimension of adaptation, which plays a central role in the context of climate change. We then review several approaches to assessing these risks, with a focus on macroeconomic and statistical modeling methods.

2.2.1 Definition

Physical risk is generally defined as the direct losses resulting from climate change hazards, that can lead to substantial economic impacts:

> "*Physical risks resulting from climate change can be event driven (acute) or longer-term shifts (chronic) in climate patterns. Physical risks may have financial implications for organizations, such as direct damage to assets and indirect impacts from supply chain disruption. Organizations' financial performance may also be affected by changes in water availability, sourcing, and quality; food security; and extreme temperature changes affecting organizations' premises, operations, supply chain, transport needs, and employee safety.*
>
> - *Acute Risk*
>   *Acute physical risks refer to those that are event-driven, including increased severity of extreme weather events, such as cyclones, hurricanes, or floods.*
> - *Chronic Risk*
>   *Chronic physical risks refer to longer-term shifts in climate patterns (e.g., sustained higher temperatures) that may cause sea level rise or chronic heat waves.*" (TCFD, 2017, page 6).

Physical risk therefore goes beyond acute, short-term events to include chronic and structural changes in the climate system that can affect the long-term viability and value of assets, businesses, and ecosystems. Despite this broader scope, the concept is still primarily associated with disasters and extreme events, as reflected in the definition provided in the most recent report by the Intergovernmental Panel on Climate Change (IPCC):

> "*[...] unmitigated climate change implies an increased potential for adverse socio-economic impacts especially in more exposed economic activities and areas (high confidence). Accordingly, physical risk refers to the component of financial risk associated with the adverse physical impact of hazards related to climate change (e.g., extreme weather events or sea level rise) on the financial value of assets such as industrial plants or real estate. In turn, these losses can translate into losses on the values of financial assets issued by exposed companies (e.g., equity/bonds) and or sovereign entities as well as losses for insurance companies. The assessment of climate financial physical risks poses challenges in terms of data, methods and scenarios. It requires cross-match scenarios of climate related hazards at granular geographical scale, with the geolocation and financial value of physical assets. The relationship between the value of physical assets (such as plants or real estate) and the financial value of securities issued by the owners of those assets is not straightforward. Further, the repercussion of climate-related hazards on sovereign risk should also be accounted for.*" (IPCC, 2022, Chapter 15, pages 1580 and 1581). "*In much of the business and financial literature, the term physical risk relates to those derived from the hazard $\times$ exposure $\times$ vulnerability framework.*" (IPCC, 2022, Annex II, page 1830).

While this framework (hazard $\times$ exposure $\times$ vulnerability) provides a useful conceptual structure, it often overlooks the adaptation dimension and its associated costs. Adaptation captures the capacity of economic agents to adjust their behavior, production processes, and investments in response to evolving climate conditions. It is therefore a crucial determinant of how physical risks translate into economic and financial losses.

To better understand the importance of adaptation, consider the wine industry, which has been and will continue to be significantly affected by climate change[7] (Schultz and Jones, 2010; van Leeuwen *et al.*, 2019). Published analyses of the Bordeaux red wine sector reveal an obvious upward trend in alcohol content over the past few decades. Wines that averaged around 12–13% alcohol by volume (ABV) in the 1990s now often exceed 13.5–14% ABV and sometimes even more in particularly warm vintages. This shift is due to increased sugar concentration in grapes caused by warmer ripening conditions, although vinification choices also play a significant moderating role. With continued global warming, there is a risk that Bordeaux wines will gradually approach the alcohol levels of fortified wines such as Madeira, potentially reaching 16–17% ABV by the end of the century. However, this outcome is far from certain because wine composition and style depend on multiple factors that will evolve with climate change, not only temperature, but also precipitation patterns, flooding, and soil composition. According to climate models, regions with the most favorable conditions for high-quality viticulture could shift northward by 2050. This could make countries such as Denmark, Norway and Sweden more suitable for producing premium wines (van Leeuwen *et al.*, 2024, page 261). Several Bordeaux estates have already begun purchasing land outside the region in anticipation of these changes. Similarly, Champagne producers have begun planting vineyards in the United Kingdom and some have expanded to Wales and Scotland, where the climate is becoming more suitable for growing grapes. These examples illustrate the decisive roles that capacity and willingness to adapt play in mitigating the long-term economic consequences of physical climate risks.

Acute risk Acute physical risks refer to extreme weather phenomena caused by events, such as storms and floods. These events can suddenly and significantly damage assets, infrastructure, and supply chains, resulting in severe economic, financial, and social repercussions. Common examples of acute events include:

1. Extreme weather events
   Hurricanes, typhoons, tropical cyclones, tornadoes, and severe windstorms can cause widespread structural damage, disrupt transportation networks, and lead to prolonged power outages.

2. Flooding
   River (fluvial) flooding from extreme precipitation, coastal flooding, and storm surges, which are exacerbated by rising sea levels; as well as flash floods, which are triggered by intense localized rainfall, can inundate properties, contaminate water supplies, and severely disrupt economic activity.

3. Hail and extreme precipitation
   Large hailstorms can damage crops, vehicles, and buildings. Cloudbursts and intense rainfall can overwhelm drainage systems and trigger landslides in vulnerable areas.

[7] Over the past few decades, the wine industry has generally benefited from moderate global warming. This has improved grape ripening, increased sugar concentration, and enhanced overall quality (Jones *et al.*, 2005). However, beyond this climatic optimum, rising temperatures pose serious threats to the wine sector. For example, Hannah *et al.* (2013) found that many traditional wine-growing regions could experience substantial losses by 2050, with some regions losing 25–73% of suitable land under a high-emission scenario (RCP 8.5 concentration pathway).

4. Short-term drought events
   Sudden reductions in precipitation or soil moisture can cause acute water shortages, affecting agricultural production, hydroelectric power generation, and industrial processes that depend on water availability.

5. Temperature extremes
   Prolonged heat waves can strain energy grids, threaten human health, reduce labor productivity, and damage heat-sensitive infrastructure. Sudden cold snaps can freeze water systems, disrupt the energy supply, and devastate crops.

6. Wildfires
   Forest, grassland, and bush fires intensified by drought, heat, and wind can destroy vast areas of property and natural ecosystems, degrade air quality over large regions, and disrupt supply chains for extended periods.

Chronic risk Chronic physical risks refer to long-term, gradual changes in climate patterns that evolve over decades. Unlike acute events, chronic risks emerge slowly and persistently, making them less visible but potentially more economically consequential due to their cumulative and often irreversible nature. These persistent changes can undermine the viability of business models and lead to prolonged social and environmental impacts. Common examples of chronic risks include:

1. Changes in precipitation patterns
   Long-term changes in rainfall patterns, such as altered seasonal distributions and intensities, can lead to chronic water scarcity, prolonged droughts and more frequent and severe flooding. These changes can affect agriculture, the water supply, and energy systems. While some regions may experience declining precipitation and extended dry periods, others may face more frequent heavy rainfall events that can overwhelm drainage systems and accelerate soil erosion.

2. Ecosystem and land degradation
   Gradual processes such as glacial retreat, loss of snowpack, deforestation, soil erosion and desertification can all diminish the availability of freshwater and reduce agricultural productivity. These changes can disrupt the provision of essential ecosystem services that support human livelihoods.

3. Ocean warming and acidification
   Persistent increases in ocean temperatures and CO_2-driven acidification affect marine ecosystems, fisheries, and coastal livelihoods. These changes can alter the availability of food resources and threatening biodiversity over the course of several decades.

4. Rising average temperatures
   Gradual increases in mean temperatures can reduce the productivity of outdoor labor, increase the demand for cooling, put a strain on energy systems, shorten the lifespan of infrastructure, reduce crop yields, and alter the suitability of regions for agriculture. Sustained warming can also expand the geographic range of disease vectors, increase heat-related mortality, and make some areas less habitable or economically viable over time.

5. Sea-level rise
   Gradual sea-level rise can result in the permanent flooding of low-lying areas, the erosion of coastlines, and the contamination of freshwater supplies by saltwater. These changes threaten the long-term viability of coastal infrastructure and human settlements.

6. Water stress
   Reduced water availability, which can be caused by altered precipitation patterns, increased evaporation, or overuse, can affect agricultural production, industrial processes, hydroelectric generation, and urban water security. Such reductions may also lead to conflicts over scarce water resources.

In Table 1, we present the classification of physical risks adopted by the European Commission under the EU Green Taxonomy. The framework identifies 28 physical risks in total (15 chronic and 13 acute hazards) grouped into four categories:

- Physical risks related to temperature (7)
- Physical risks related to wind (4)
- Physical risks related to water (10)
- Physical risks related to solid mass and soil (7)

This classification has also been adopted by WRI and CBI (2019). However, alternative taxonomies of physical climate risks exist, though they are often partial or less comprehensive. For example, the U.S. EPA framework distinguishes between acute and chronic hazards but does not provide a detailed categorization by hazard type. In contrast, the OECD builds on the 28 climatic impact-driver categories developed in the IPCC's Sixth Assessment Report (IPCC, 2022; Ruane *et al.*, 2022) and groups them into acute and chronic risk categories (Noels *et al.*, 2024).

2.2.2 The hazard/exposure/vulnerability framework

From a financial perspective, the ultimate goal of physical risk modeling is to quantify the impact of climate change on national economies, corporate performance, and investment portfolio returns. The framework generally used is the hazard/exposure/vulnerability:

$$\text{Risk} = f\left(\text{hazard} \times \text{exposure} \times \text{vulnerability}\right)$$

According to the IPCC AR6 Glossary[8], the components are defined as follows:

- Hazard is "*the potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems and environmental resources.*"
- Exposure is "*the presence of people; livelihoods; species or ecosystems; environmental functions, services, and resources; infrastructure; or economic, social, or cultural assets in places and settings that could be adversely affected.*"
- Vulnerability is "*the propensity or predisposition to be adversely affected. Vulnerability encompasses a variety of concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt.*"
- Risk is "*the potential for adverse consequences for human or ecological systems, recognising the diversity of values and objectives associated with such systems.*"

[8]Source: `https://apps.ipcc.ch/glossary`.

Table 1: Classification of climate-related hazards by type and duration (EU taxonomy)

	Temperature related	Wind related	Water related	Solid mass related
Chronic	Changing temperature (air, freshwater, marine water)	Changing wind patterns	Changing precipitation patterns and types (rain, hail, snow/ice)	Coastal erosion
	Heat stress		Precipitation and/or hydrological variability	Soil degradation
	Temperature variability		Ocean acidification Saline intrusion	Soil erosion
	Permafrost thawing		Sea-level rise Water stress	Solifluction
Acute	Heat wave	Cyclone, hurricane, typhoon	Drought	Avalanche
	Cold wave/frost	Storm (including blizzards, dust and sandstorms)	Heavy precipitation (rain, hail, snow/ice)	Landslide
	Wildfire	Tornado	Flood (coastal, fluvial, pluvial, ground water) Glacial lake outburst	Subsidence

Source: TEG (2020) & European Commission[a] (2021, Appendix A, page 190).

[a]Commission Delegated Regulation (EU) 2021/2800 (Climate Delegated Act — Annex I) under the Regulation (EU) 2020/852 (EU Taxonomy Regulation)

While hazard, exposure, and vulnerability are relatively well-defined, risk is a more complex concept to measure. In the context of climate change, risk usually refers to quantifiable metrics, such as the frequency, severity, or magnitude of potential losses. For example, consider labor productivity losses due to heat stress. In this case, the hazard is the occurrence of extreme heat events or sustained high temperatures. Exposure corresponds to the percentage of the labor force working in heat-sensitive sectors, such as construction, agriculture, and manufacturing, as well as in regions prone to high temperatures. Vulnerability reflects factors such as the availability of cooling infrastructure and labor protection measures, as well as the adaptive capacity of workers and employers. The resulting risk can be quantified as expected losses in labor productivity, expressed as a percentage of GDP, a monetary value in dollars, or reduced working hours. However, translating physical risk metrics into monetary losses is not straightforward. Using the hazard/exposure/vulnerability framework, the most direct approach to calculating labor productivity impacts is first to estimate the number of lost working hours, then to multiply this number by the average wage to obtain a dollar value. This method requires a valuation function that converts physical risk metrics into monetary terms. While this valuation function may appear simple at first, it becomes more complex when considering indirect and cascading effects. Beyond direct impacts, we must account for transmission channels throughout the economy. For instance, labor productivity losses can impact a country's public debt, resulting in additional losses that intensify the initial impact. Distinguishing between physical risk metrics and financial losses requires an additional analytical layer beyond the standard hazard/exposure/vulnerability framework:

$$\text{Loss} = g\left(\text{Risk}\right)$$

where Risk is the metric expressed in physical units, g is the valuation function, and Loss is the financial impact in monetary terms. The function g can be simple, as in the previous example, but it is generally complex when considering acute events, such as hurricanes or floods.

Estimating financial losses from climate change requires several key steps. First, a climate model is needed to project future climate conditions. Model choices range from simple energy-balance models (EBMs), to integrated assessment models (IAMs) and Earth-system models of intermediate complexity (EMICs), and up to high-complexity general circulation models (GCMs), which are the standard tools for modeling climate hazards and form the basis for most physical risk assessments (Roncalli, 2026, Chapter 12). The second step is to estimate exposure and vulnerability using separate yet complementary modeling frameworks. Exposure is typically determined by identifying and mapping assets, populations, and economic activities in areas susceptible to hazards. This process uses data from land-use databases, infrastructure inventories, and satellite observations. A vulnerability assessment focuses on the sensitivity of these elements to climate hazards. This assessment considers factors such as building standards, adaptive capacity, socioeconomic conditions, and existing protective infrastructure. Then, exposure and vulnerability estimates are integrated spatially with hazard projections using geographic information systems and geolocation techniques. This process links climatic hazards with the physical and socioeconomic characteristics of specific sites. It generally requires large datasets and specialized statistical methods. Finally, economic and financial models translate physical risk metrics into monetary losses. These models range from simple damage functions, which directly relate physical impacts to economic costs, to computable general equilibrium models, which simulate the propagation of climate shocks through the entire economy via supply chains, price adjustments, and behavioral responses in consumption and investment. The appropriate model depends on the scope of the analysis, the sectors considered, and whether direct, indirect, or macroeconomic losses are to be estimated.

2.2.3 Physical risk data and modeling

Two main types of climate data are used for modeling physical risks to describe past and present conditions. The first category consists of historical observational data, which are direct measurements of climate variables, such as air temperature, precipitation, wind speed, and humidity. These data have some limitations such as irregular spatial coverage, interruption of temporal continuity, and the presence of instrumental errors. The second type of climate data consists of reanalyses. These datasets estimate historical climate variables by combining observations with numerical climate models using data assimilation techniques. Unlike raw observations, reanalyzed data are standardized, spatially complete, and temporally consistent, but the accuracy of these data depends heavily on the density and quality of the underlying observations. Examples of observational datasets with global coverage for temperature include Berkeley Earth, HadCRUT5, and GISTEMP v4. For precipitation, examples include GPCC Full Data and GPCP. Reanalysis datasets include ERA5, MERRA-2, and CFSR for the atmospheric domain, and CERA-20C and ECCO v4 for the oceanic domain. More detailed examples and information on these datasets are reported in Roncalli (2026, Section 12.2.2, page 1156). While observational datasets rely on a few variables, reanalysis datasets generally include hundreds of physically consistent variables derived from numerical models. For example, the ERA5 dataset provides 262 main single-level variables, covering not only temperature, precipitation, and pressure, but also soil moisture, snow depth, cloud properties, lake variables, surface albedo, and numerous other atmospheric, oceanic, and land surface parameters.

Other datasets provide forward-looking information for assessing future climate risks, as projected changes in the frequency and spatial distribution of tropical cyclones and heat waves. These datasets are climate-model outputs used in scenario-based physical risk analyses to simulate how the climate system may evolve under different greenhouse gas emission scenarios. Similar to reanalysis datasets, climate model outputs offer comprehensive spatial coverage and a full range of physically consistent variables extending decades into the future. However, projection results should be interpreted taking into account differences in model structure and in emissions scenarios. A large number of variables are generated within the CMIP6 framework and organised into standardised MIP tables, *e.g.*, *Amon* with 75 atmospheric montly variables, *Omon* with 292 ocean montly variables, etc.

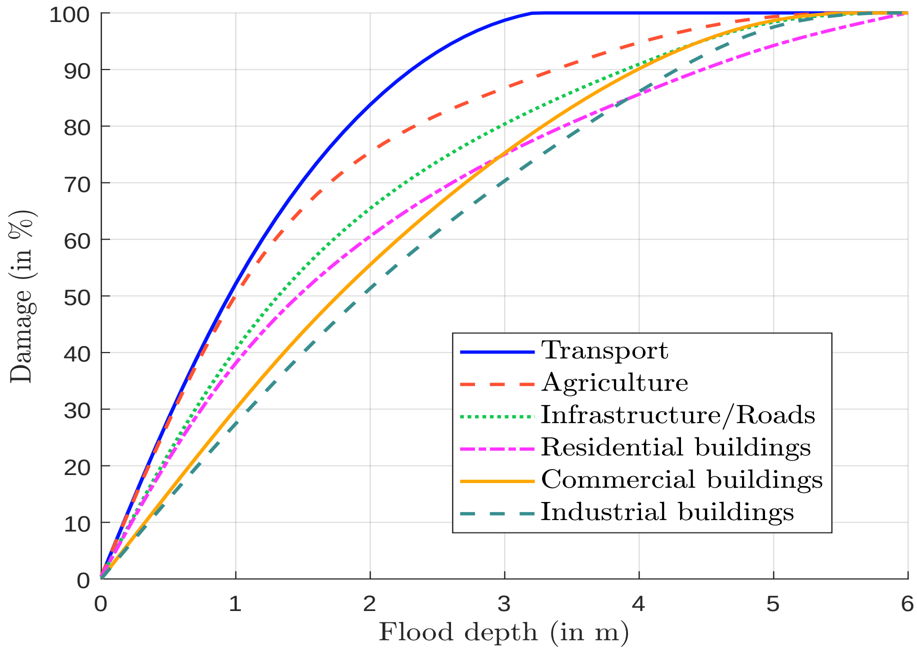
In addition to the datasets described above, there are also specific physical-risk data aligned with the hazard/exposure/vulnerability framework, but since these data are primarily historical, there is generally some overlap with the observational and reanalysis datasets. These specific datasets combine climate-related hazard data (historical maps, event footprints and hazard characteristics projections), climate-related exposure (gridded population, building footprints, infrastructure inventories, land use and land cover maps, economic and ecological assets, agricultural production) and climate-related vulnerability (building integrity coefficients, cost-benefit ratio of adaptation options, age structure and poverty levels)[9]. The ultimate objective of using vulnerability data is to construct damage functions. A damage function can be viewed as a standardized model of the form:

$$D(t) = f\left(X_1(t), \ldots, X_m(t)\right)$$

where $X_1(t), \ldots, X_m(t)$ denote relevant characteristics or input variables. Typically, $D(t)$ represents a damage rate, meaning that $D(t) \in [0, 1]$. There are two main categories of damage functions. The first category comprises tabulated or non-parametric functions derived

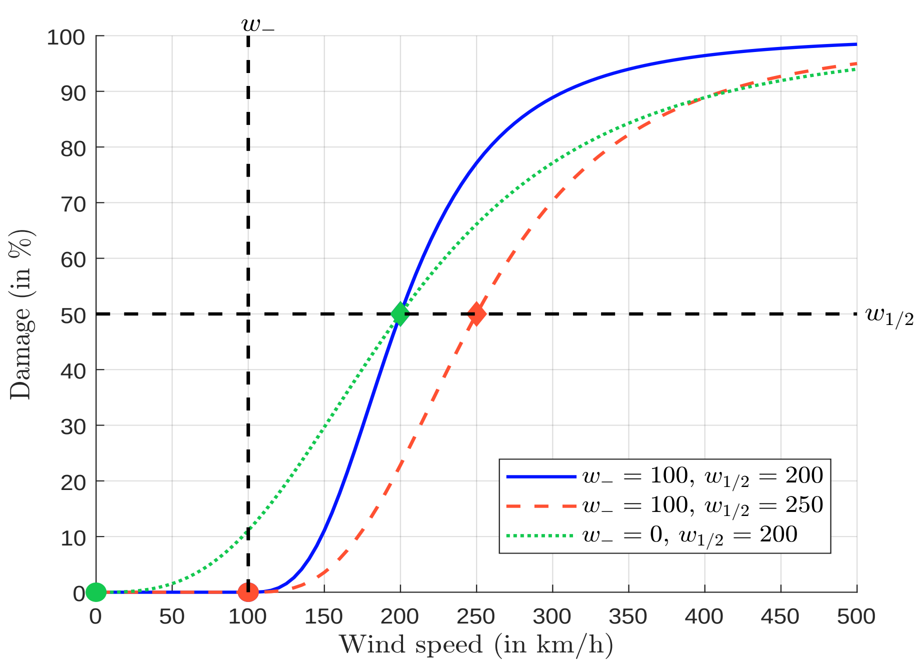
[9] Large examples of data sources to measure climate hazards, exposure and vulnerability of physical assets are provided in Roncalli (2026, Chapter 12).

Figure 4: Flood damage functions for the European region



Source: Huizinga *et al.* (2017) and Roncalli (2026, Figure 12.6, page 1174).

Figure 5: Example of wind damage function



Source: Emanuel (2011) and Roncalli (2026, Figure 12.8, page 1175).

from observed data. For example, a flood damage function can be expressed as follows:

$$D(t) = f(\text{depth}, \text{duration})$$

where $D(t)$ represents damage in $\$/\text{m}^2$, depth is the water depth in centimeters, and duration is the flood duration in hours. Given gridded values of depth and duration, one can empirically estimate the average damage ratio. The second category consists of parametric functions, as the sigmoidal function for wind damage proposed by Emanuel (2011):

$$D(t) = \frac{\omega^3}{1 + \omega^3}$$

with:

$$\omega = \frac{\max(w - w_-, 0)}{w_{1/2} - w_-}$$

where w is the wind speed, w_- is the threshold below which no damage occurs, and $w_{1/2}$ is the wind speed at which the damage function reaches 50%. Figure 4 illustrates non-parametric flood damage functions by depth for Europe as estimated by Huizinga *et al.* (2017) while Figure 5 shows the wind damage function of Emanuel (2011) assuming different values of w_- and $w_{1/2}$.

2.2.4 From macroeconomic to granular modeling of physical climate risk

Climate change and its associated risks exert a substantial impact on the global economy and financial stability. Consequently, following the seminal work of Nordhaus and Boyer (2000), numerous studies focused on financial loss models for physical climate risk. Damage functions are used in several integrated assessment models, but the damage estimates can vary significantly depending on the methods and approaches employed. Table 2 show the percentage of damages projected by several models for temperature increases of 2°C and 3°C under current policy scenarios for the years 2050 and 2100 (NGFS, 2024).

Table 2: Damage estimates across damage functions

Study	2°C	3°C	Study	2°C	3°C
Nordhaus and Boyer (2000)	1%	2%	Burke *et al.* (2015)	8%	14%
Tol (2009)	1%	3%	Howard and Sterner (2017)	3%	8%
Pindyck (2012)	4%	9%	Kompas *et al.* (2018)	1%	2%
Weitzman (2012)	1%	3%	Kalkuhl and Wenz (2020)	2%	5%
Dell *et al.* (2012)	4%	22%	Kahn *et al.* (2021)	3%	8%
Tol (2014)	1%	2%	Waidelich *et al.* (2024)	4%	8%
Nordhaus (2014)	1%	2%	Bilal and Känzig (2024)	19%	44%
Dietz and Stern (2015)	2%	13%	Kotz *et al.* (2024)	14%	33%

Source: NGFS (2024, Table 3, page 14).

As noted by Jean *et al.* (2025), more recent studies tend to estimate greater losses resulting from climate change. By using global mean temperature and including both chronic and acute risks, Bilal and Känzig (2024) estimate macroeconomic impacts up to six times larger than those reported in earlier studies. They find that a 1°C rise in global temperature could lead to a loss of up to 12% of global GDP. Rather than focusing solely on average temperature, Waidelich *et al.* (2024) incorporate a broader set of variables, including the number of wet days, extreme daily rainfall, precipitation variability, and total precipitation. When these factors are included, the study estimates that a 3°C increase in global mean temperature could reduce global GDP by as much as 10%. The results also reveal heterogeneous effects across countries. Losses tend to be larger in poorer nations and in low-latitude regions. In line with this study, Kotz *et al.* (2024) not only incorporate average temperatures but also include precipitation, daily variability, and extreme events in their damage-function estimation. A key innovation of their approach is the explicit inclusion of lagged effects to capture persistence in climate impacts. The model yields substantially larger damage estimates than prior studies, projecting a contraction of the global economy of about 19% over the next 26 years.

Damage functions are designed to produce aggregated regional or global loss estimates and therefore serve well for macroeconomic and policy assessment, but they are ill-suited for financial applications that require asset-level precision. Their limited granularity makes them not appropriate for company- or asset-level exposure and vulnerability analysis. For that reason, commercial data vendors have developed higher-resolution metrics to quantify exposure and vulnerability at finer (site, firm or asset-level) scales. Table 3 lists several major providers of physical climate-risk data. Most of these data vendors offer asset- and company-level exposure and vulnerability metrics that cover a broad set of climate hazards (*e.g.*, flood, heat, wildfire, tropical cyclone, drought). These products are typically scenario-based, produced under alternative greenhouse-gas emission pathways (and associated climate projections). Typically, vendors also provide multi-decade projections, enabling users to assess how risk evolves and rises over time. Note that all these physical risk metrics are derived from scoring systems rather than from direct data measurement. As a result, they are highly sensitive to modeling assumptions, scenario selection, projected horizons, and aggregation methods. Furthermore, most vendor models are continually updated and refined, thus scores and projections can change over time.

In addition to commercial data providers, it is worth mentioning the methodological framework developed by several EU bodies to integrate climate-related physical risks into financial-stability monitoring and prudential supervision. Four types of physical-hazard indicators for financial-institution portfolios are defined, all expressed as percentages of portfolio value. Two indicators are based on physical-risk level categories — risk scores (RS) and potential exposure at risk (PEAR) — while the other two are based on estimates of expected losses — normalized exposure at risk (NEAR) and collateral-adjusted exposure at risk (CEAR).

Other useful and popular datasets used for measuring physical risk are provided by the academic research, such as EM-DAT (Emergency Events Database), that focuses on the assessment of natural disaster impact and ND-GAIN[10]. Furthermore, academics have developed sophisticated tools for measuring physical risk. One notable example is CLIMADA, a free and open-source software framework[11] (Aznar-Siguan and Bresch, 2019), used for climate risk assessment and adaptation planning. Another important academic contribution is the development of comprehensive methodologies for quantifying potential financial losses from physical climate risks. The seminal work of Battiston *et al.* (2017) introduces a framework for stress-testing financial portfolios against climate risks, providing a conceptual basis for translating climate shocks into financial losses. Early research focuses on specific hazards, such as cyclones (Le Guenedal *et al.*, 2022), droughts (Huynh *et al.*, 2020), floods (Mandel *et al.*, 2021), and wind storms (Koks and Haer, 2020). Other studies examined particular regions, such as Mexico (Bressan *et al.*, 2024) and Florida (Calabrese *et al.*, 2024). More recently, Mandel *et al.* (2025) introduced CLIMACRED, a global model that integrates multiple hazards and regions, advancing comprehensive climate risk assessment by explicitly linking compound physical events to financial assets.

[10] This database is described in details in Section 3.2.1 on page 45.
[11] Its website is `https://climada.ethz.ch`.

Table 3: Major providers of physical climate risk data

Data provider	Coverage	Hazards and scenarios	Metrics
Bloomberg Riskthinking.AI[a]	Nearly 50 000 companies, over 1 million physical assets worldwide	Different climate scenarios, projections up to 2050	Physical risk exposure metric at company and individual assets levels
Carbon4 Finance[b]	210 countries, 60+ sectors, coverage of most asset classes	7 direct hazards, 3 IPCC scenarios, 2 time horizons	Aggregated risk rating and hazard-specific ratings
First Street[c]	Properties and infrastructures, mainly in the USA	Present and future	Property-level risk statistics (peril exposure, climate risk score, financial impact), simulations of buildings damage and downtime
Jupiter Intelligence[d]	Global coverage	Multiple perils and scenarios, 5-year increments, up to 2100	Hazard scores, direct financial impact metrics, current and future climate risk at asset and portfolio/company level
Moody's[e]	70 countries, 22 000+ entities, 10 million+ facilities	8 hazards (acute and chronic), several scenarios	Forward-looking exposure metrics
MSCI[f]	800 000+ asset locations for 12 000+ companies	28 distinct physical hazards under several climate scenario pathways	Physical risk metrics at company level
S&P Global Sustainable1[g]	Global coverage of 200+ countries, 70 000+ companies, 7 million+ asset locations	10 physical hazards, 4 scenarios, several decades up to 2090	Exposure and sensitivity scores, financial impact estimates, at company and asset level
Verisk Maplecroft[h]	198 countries	35 hazards and issues (17 climate hazards) across 7 time periods, 3 climate scenarios	300+ hazard risk indices, socioeconomic vulnerability indices, transition-risk assessment

Sources (websites accessed 17/02/2026):

[a] https://www.riskthinking.ai

[b] www.carbon4finance.com/product/physical-risks

[c] https://firststreet.org

[d] www.jupiterintel.com/climatescore-global

[e] www.moodys.com/web/en/us/capabilities/physical-transition-risk/insurance.html

[f] www.msci.com/data-and-analytics/climate-solutions/physical-risk-solutions

[g] www.spglobal.com/sustainable1/en/solutions/physical-climate-risk-solutions

[h] www.maplecroft.com/data/country-risk-data/climate-risk-data

3 Portfolio management

3.1 Physical vs. transition risk in equity portfolios

In this section, we examine the impact of incorporating physical climate risk into equity portfolios. To do so, we use S&P physical risk scores. After analyzing and comparing these scores with conventional transition risk scores, we incorporate physical risk into a standard mean-variance portfolio optimization framework. The objective of the optimization is to replicate an equity benchmark while maintaining low tracking error volatility. Then, we compare portfolios optimized using physical risk metrics with those optimized using transition risk metrics. This analysis is conducted across two investment universes: the MSCI World Index and the MSCI Emerging Markets Index.

3.1.1 Physical scores

Exposure scores We recall that the assessment of physical climate risk is based on the hazard/exposure/vulnerability framework:

$$\text{Risk} = f\left(\text{hazard} \times \text{exposure} \times \text{vulnerability}\right)$$

The physical risk scores provided by S&P Global Sustainable1 are constructed using this framework (S&P Global, 2025). The S&P methodology considers ten climate hazards: (1) coastal flooding, (2) river flooding, (3) pluvial flooding, (4) extreme heat, (5) extreme cold, (6) tropical cyclones, (7) wildfires, (8) water stress, (9) drought, and (10) landslides. As a result, the methodology focuses more on acute risks than chronic risks. To measure exposure, S&P relies on an asset-based classification. Based on these data, S&P Global (2025) maps asset values to corporate owners[12], and derives two types of physical risk metric:

1. Physical risk exposure score
2. Physical risk financial impact

The exposure score is a measure of a company's exposure to climate hazards at a given point in time. It does not depend on the specific characteristics of the assets. The score can be aggregated at the portfolio level to evaluate the contribution of individual assets, and it is expressed on a scale from 1 (lowest exposure) to 100 (highest exposure). The financial impact metric estimates the potential financial consequences of changes in climate hazard exposure relative to a baseline scenario while accounting for asset-specific characteristics. It is expressed as expected financial losses measured as a percentage of asset value. The difference between the exposure score and the financial impact metric incorporates a loss impact (or damage) function. Both metrics are first calculated at the hazard level and then aggregated to form a composite physical risk score at the company level[13]. In what follows, we focus exclusively on physical risk exposure scores to ensure comparability with the transition risk analysis. In the case of transition risk, metrics typically used by portfolio managers, such as carbon intensity and greenness, measure exposure rather than realized or expected costs. In this sense, carbon and green intensity can be interpreted as measures of exposure to transition risk. For consistency, therefore, we use physical risk exposure measures rather than financial impact metrics.

[12]This means that physical scores are first calculated for each hazard at asset level. These are then aggregated at the corporate level using the decision tree shown in S&P Global (2025, Figure 3, page 16).

[13]The physical risk exposure score at company level is given by $\boldsymbol{\mathcal{PE}} = 100 - 100 \times \exp\left(c\sum_{j=1}^{10}\boldsymbol{\mathcal{PE}}_j\right)$, where $\boldsymbol{\mathcal{PE}}_j$ is the physical risk exposure score for hazard j and c is a scaling parameter.

Remark 2. *In practice, S&P Global (2025) calculates two physical risk scores:*

1. *A composite physical risk score $\mathcal{PE}$ (ranging from 1 to 100), which captures a company's combined exposure to all ten climate hazards. The score is first computed at the asset or location level and then aggregated at the company level using a weighted average across multiple locations[14].*

2. *A sensitivity-adjusted composite physical risk score (ranging from 1 to 100), which extends the composite score by incorporating the company's sensitivity to different climate hazards. For water stress and drought hazards, sensitivity is proxied by the company's water intensity. For extreme heat and extreme cold hazards, sensitivity is measured using labor intensity. For the remaining six hazards, company sensitivity is approximated by tangible asset intensity. The hazard-specific sensitivity-adjusted scores are then aggregated into a single synthetic score $\mathcal{SE}$ using an exponentially aggregation function. The resulting synthetic score $\mathcal{SE}$ is used as a proxy for the physical vulnerability risk of the company.*

Both metrics are available under different climate scenarios based on IPCC RCP/SSP pathways:

- Low climate change scenario (SSP1-2.6)
  An aggressive mitigation scenario in which total greenhouse gas emissions decline to net zero by 2050. This results in a global average temperature increase of 1.3–2.4°C by 2100, which is consistent with the Paris Agreement targets.

- Medium climate change scenario (SSP2-4.5)
  A strong mitigation scenario in which total greenhouse gas emissions stabilize at current levels until 2050, before declining through 2100. This scenario projects that global average temperatures will rise by 2.1–3.5°C by 2100.

- Medium-high climate change scenario (SSP3-7.0)
  Limited mitigation scenario in which total greenhouse gas emissions double by 2100, with global average temperatures rising by 2.8–4.6°C by 2100.

- High climate change scenario (SSP5-8.5)
  Low mitigation scenario in which total greenhouse gas emissions triple by 2075, with global average temperatures rising by 3.3–5.7°C by 2100.

The metrics are evaluated for each hazard-scenario combination across multiple time horizons from 2020 to 2090. The following analysis focuses exclusively on the medium (SSP2-4.5) and high (SSP5-8.5) climate change scenarios because the low scenario is no longer considered realistic given current emissions trajectories. Moreover, the medium-high scenario results can be approximated as intermediate between the medium and high scenarios. Regarding time horizons, we concentrate on three reference decades:

- 2030 represents a medium-term horizon, enabling investors to assess the materiality of physical over investment time frames relevant to tactical asset allocation;

- 2050 corresponds to a long-term horizon (approximately 25 years forward), that aligns with the typical periods used by institutional investors for strategic asset allocation and is consistent with net-zero commitment timelines;

- 2090 provides a very long-term perspective, that allows us to examine how physical risks evolve and their implications for future asset management.

[14]See Footnote 13 on page 27.

Figure 6: Histograms of the exposure score $\mathcal{PE}$ (MSCI World Index)

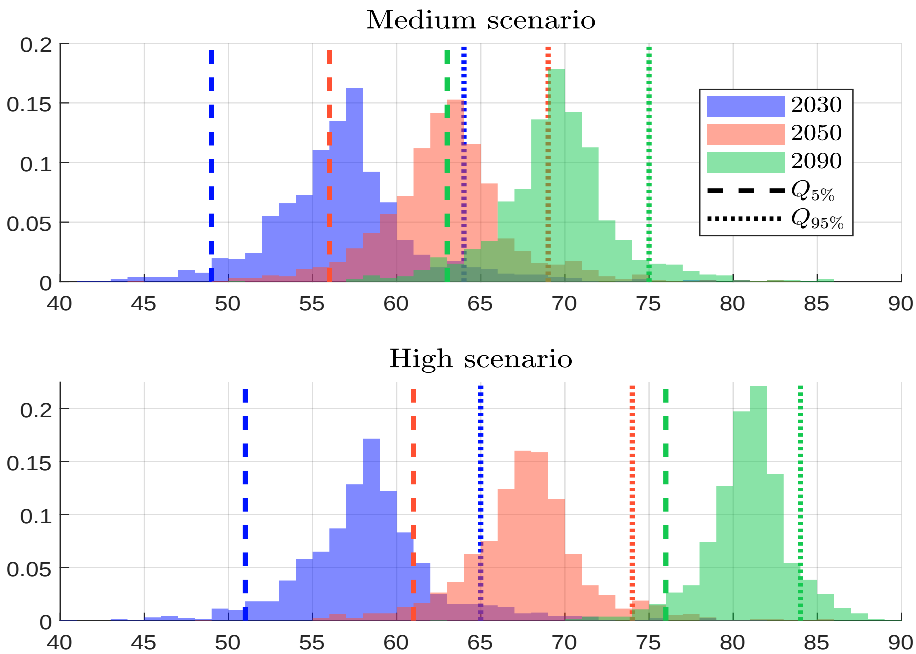


Figure 7: Histograms of the sensitivity score $\mathcal{SE}$ (MSCI World Index)

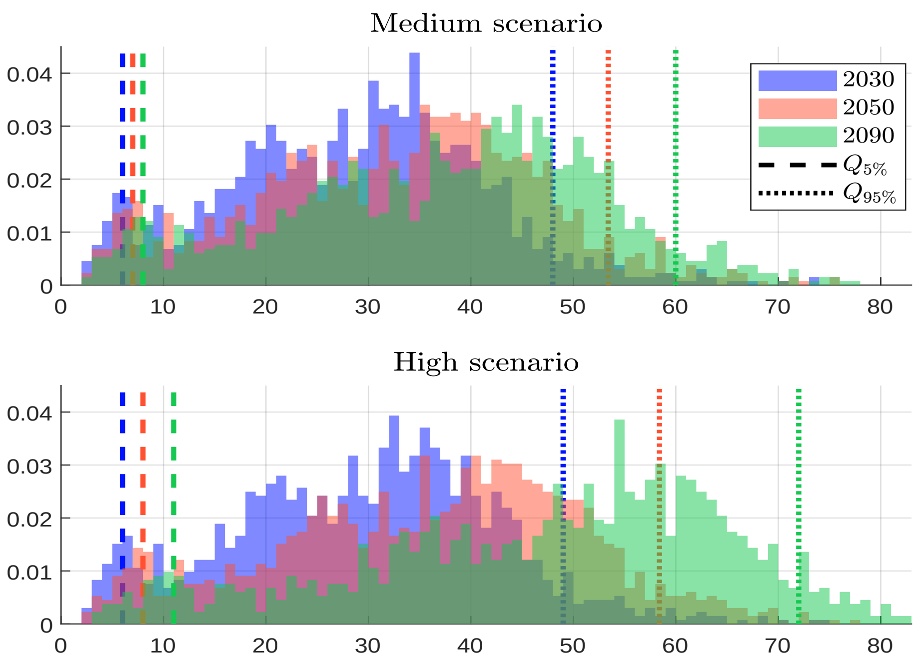


Figure 6 shows how the composite physical risk exposure score is distributed among companies included in the MSCI World Index. This score increases systematically as the reference decade and risk scenario severity progress. For example, under the medium scenario, the average exposure score increases from 56.3 in 2030 to 62.4 in 2050, and then to 69.0 in 2090. Under the high scenario, the corresponding averages are 57.9, 67.2, and 80.4, respectively. The incremental increases between the medium and high scenarios are 1.6, 4.8, and 11.4 for the time horizons of 2030, 2050, and 2090, respectively. These results indicate that physical risk exposure grows over time and accelerates as scenario severity increases. Despite this upward trend, exposure scores exhibit limited dispersion within each time horizon and risk scenario. This suggests that companies tend to cluster around similar exposure levels. For instance, the interquartile range $Q_3 - Q_1$ is approximately 4 (Table 4).

Table 4: Statistics of the exposure and sensitivity scores (MSCI World Index)

Metric	Statistic	Medium scenario			High scenario		
		2030	2050	2090	2030	2050	2090
$\mathcal{PE}$	Mean	56.3	62.4	69.0	57.9	67.2	80.4
	Q_1	54.0	60.0	67.0	60.0	69.0	82.0
	Q_3	58.0	64.0	71.0	56.0	65.0	79.0
	$Q_3 - Q_1$	4.0	4.0	4.0	4.0	4.0	3.0
$\mathcal{SE}$	Mean	28.1	32.2	37.0	29.2	35.6	46.7
	Q_1	19.0	22.0	26.0	38.0	46.0	60.0
	Q_3	36.0	42.0	48.0	20.0	25.0	35.0
	$Q_3 - Q_1$	17.0	20.0	22.0	18.0	21.0	25.0

Figure 7 shows the distribution of the sensitivity-adjusted composite physical risk exposure score. As expected, this sensitivity score exhibits the same general patterns as the unadjusted exposure score, increasing with both time horizon and scenario severity. However, it displays two important distinguishing features. First, the sensitivity score is systematically lower than the exposure score. This reflects the fact that the sensitivity score incorporates asset-specific vulnerability characteristics and can be conceptualized as the product of the exposure score and a vulnerability factor. For instance, a company with 50% exposure could have 10% sensitivity if its vulnerability is 20%, meaning its assets are relatively resilient to the hazards[15]. Second, the sensitivity score demonstrates substantially greater dispersion than the exposure score. The interquartile range $Q_3 - Q_1$ of the sensitivity score is approximately five times larger than that of the exposure score (Table 4), indicating considerable heterogeneity in how companies are affected by physical climate risks despite similar exposure levels. This wider dispersion arises from differences in asset characteristics, infrastructure quality, and adaptation measures across companies. Consequently, the sensitivity score is expected to produce more differentiated assessments of physical risk at the company level. However, the temporal progression — the rate of increase across time horizons — is less pronounced for the sensitivity score than for the exposure score.

Sector-level analysis of the two physical risk scores for the 2030 time horizon is presented in Figures 8 and 9. The exposure score indicates low variation between sectors, with median scores ranging from 55 to 57 across all 11 sectors. Exposure scores are distributed relatively uniformly. However, there are notable exceptions. The Energy sector exhibits greater dispersion due to the geographic diversity of its infrastructure and resource extraction activities, while the Information Technology sector shows lower dispersion, consistent with its

[15] Similarly, a highly exposed company may have near-zero sensitivity if its assets are largely not vulnerable to the hazards.

Figure 8: Boxplot of the exposure score $\mathcal{PE}$ per GICS sector (MSCI World Index, 2030 medium scenario)

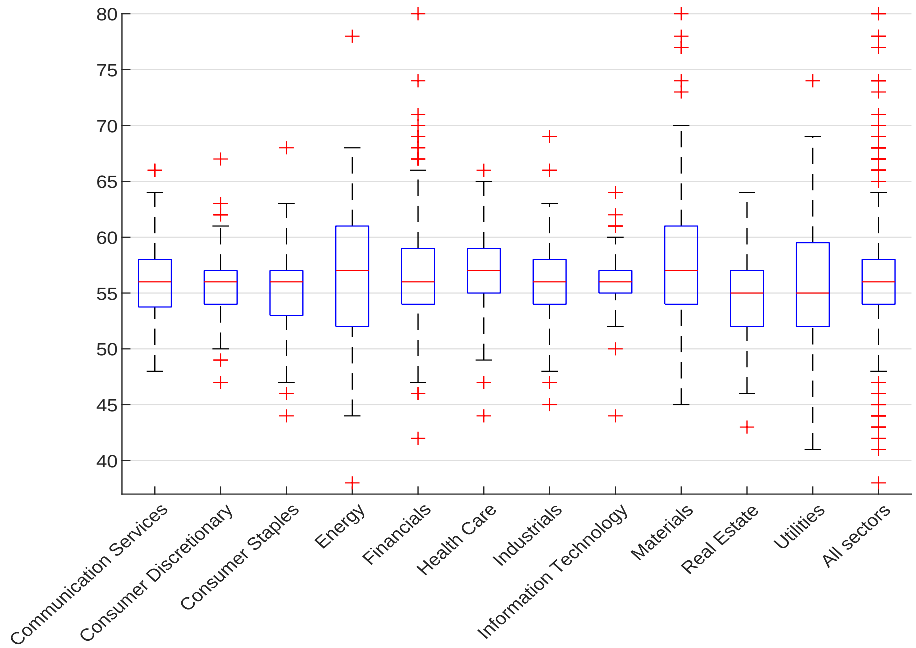
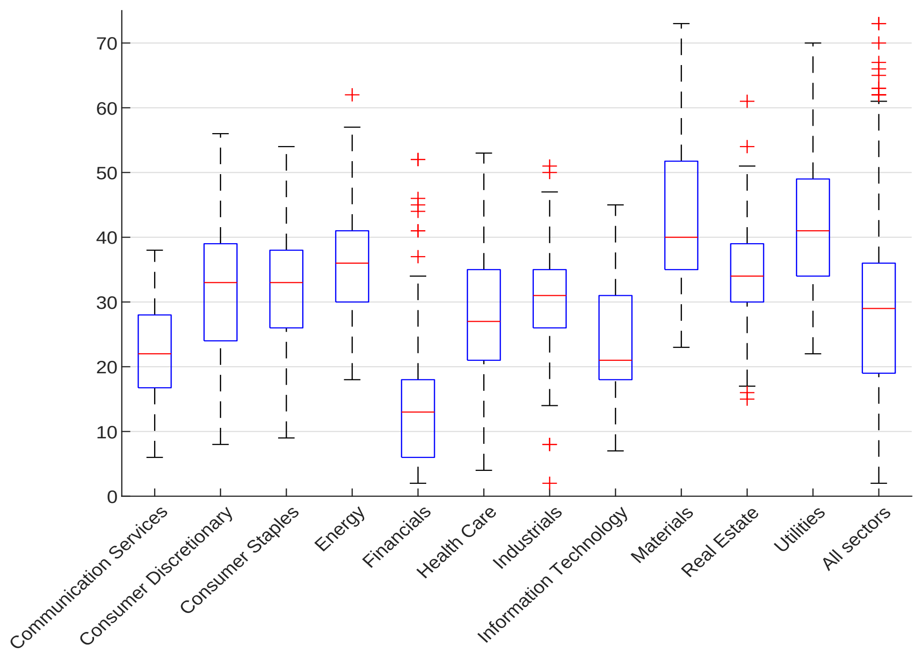


Figure 9: Boxplot of the sensitivity score $\mathcal{SE}$ per GICS sector (MSCI World Index, 2030 medium scenario)



relatively concentrated geographic footprint. In contrast, the sensitivity score demonstrates substantial inter-sector heterogeneity, with median scores ranging from 13 for Financials to 41 for Utilities. This pronounced dispersion reflects fundamental differences in asset characteristics and operational models across sectors.

Table 5: Pearson correlation between physical risk and transition risk scores (MSCI World Index, 2030 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$	$\mathcal{GI}$
Medium	$\rho(\mathcal{PE},\mathcal{TR})$	−1.20	9.02	−2.80	7.21	7.16	−9.00
	p-value	66.25	0.10	30.99	0.87	0.92	0.10
High	$\rho(\mathcal{PE},\mathcal{TR})$	−2.00	9.01	−3.40	6.48	6.32	−8.89
	p-value	46.82	0.10	21.68	1.85	2.15	0.12
Medium	$\rho(\mathcal{SE},\mathcal{TR})$	27.03	26.13	32.81	0.12	4.93	24.44
	p-value	0.00	0.00	0.00	96.41	7.31	0.00
High	$\rho(\mathcal{SE},\mathcal{TR})$	26.41	26.03	32.91	−0.03	4.71	24.77
	p-value	0.00	0.00	0.00	99.06	8.72	0.00

Relationship between physical risk exposure and transition risk exposure metrics
This paragraph examines the relationship between transition risk and physical risk exposures to determine the extent to which these two dimensions of climate risk are interrelated. Let $\mathcal{TR}$ and $\mathcal{PR}$ denote transition and physical risk exposure scores. We calculate the Pearson correlation coefficient $\rho(\mathcal{PR},\mathcal{TR})$ and test the null hypothesis $H_0 : \rho(\mathcal{PR},\mathcal{TR}) = 0$ using the associated p-value. We assess transition risk exposure using two complementary metrics: carbon intensity (measured across different emission scopes) and green intensity, proxied by the green revenue share (Roncalli, 2026). Correlation analysis reveals distinct patterns depending in the relationship between transition risk metrics and physical risk scores depending on the physical risk measure employed. For the physical risk exposure score, all Pearson correlation coefficients with carbon intensity measures are close to zero, indicating weak linear relationships between these variables (Table 5). The p-values indicate that these correlations are statistically significant in most cases, except for Scope 1 and Scope 3 upstream emissions. The association between the exposure score and green intensity is negative and small in magnitude, but statistically significant at the 1% confidence level. This suggests that companies with higher green revenue shares exhibit marginally lower physical risk exposure ($\rho(\mathcal{PE},\mathcal{GI}) = -9\%$ under the medium climate change scenario). In contrast, the sensitivity score exhibits different patterns. It demonstrates positive and statistically significant associations with all carbon intensity measures except for Scope 3 downstream emissions[16] (Table 5). Notably, a positive and statistically significant relationship also emerges with green intensity ($\rho(\mathcal{SE},\mathcal{GI}) = 24.44\%$ under the medium climate change scenario), suggesting that companies with higher green revenue shares tend to be more sensitive to physical climate risks[17]. These various results are corroborated when using Spearman correlations (see Table 26 on page 69). Specifically, the Spearman correlation with the physical risk exposure score is consistently not statistically significant at the 1% level, whereas the Spearman correlation with the physical risk sensitivity score is consistently significant at the 1% level. Moreover, the results remain qualitatively similar when using the 2090 time horizon instead of the 2030 time horizon.

[16] Consistent results are obtained using Spearman rank correlations instead of Pearson correlations.

[17] This counterintuitive finding may be due to the fact that green economy sectors, such as renewable energy generation, sustainable agriculture, and water management, tend to have asset-intensive business models. These sectors have significant fixed infrastructure that is directly exposed to climate hazards. Despite their favorable transition risk profiles, this increases their sensitivity to physical risk.

Sector and country analysis Considering the sector composition of the MSCI World Index, the two largest sectors by number of constituents[18] are Financials and Industrials (Table 6). However, the largest sectors by market weight are Financials and Information Technology. The weighted average carbon intensity[19] is highest in Industrials and Energy, and lowest in Health Care and Communication Services. As previously observed, the differences in weighted average exposure scores across sectors are modest. Materials is slightly above the cross-sector mean for both the 2030s and 2090s, while Real Estate is slightly below, but the range is relatively low from 54.9 and 59.5 for the 2030 medium scenario. In contrast, the sensitivity score reveals clearer sectoral patterns for both timeframes (2030 and 2090). Financials show the most favourable sensitivity values (14.4 for the 2030 scenario), followed by Information Technology (17.6), while Materials and Utilities record the least favourable values (43.4 and 44.2, respectively). Concerning the distribution of green intensity, Real estate and Utilities have the largest green revenue share, while Financials and Health Care have the smallest. This relationship is confirmed by correlation analysis. In summary, exposure varies only marginally across sectors, whereas sensitivity shows much greater variation, which has important implications for sector allocation and risk management. Based on these results, it is difficult to identify clear correlation patterns between transition and physical climate risks at the sector level.

Table 6: Weighted mean of climate risk measures per sector (MSCI World Index, medium scenario)

Sector	n_j	b_j	$\mathcal{CI}_{1-3,j}$	$\mathcal{PE}_j^{2030}$	$\mathcal{SE}_j^{2030}$	$\mathcal{PE}_j^{2090}$	$\mathcal{SE}_j^{2090}$	$\mathcal{GI}_j$
Communication Services	65	8.7	107	57.9	20.1	69.5	27.5	5.7
Consumer Discretionary	128	9.9	443	56.5	32.9	68.6	43.1	22.7
Consumer Staples	98	5.5	595	57.3	31.6	69.7	41.2	1.0
Energy	50	3.5	3 982	57.5	35.7	69.1	45.5	6.2
Financials	235	16.4	1 908	57.1	14.4	69.6	19.0	0.6
Health Care	121	10.0	99	57.4	22.6	69.8	30.3	0.7
Industrials	255	10.9	4 305	56.7	30.3	69.3	39.9	21.2
Information Technology	137	27.4	317	58.2	17.6	70.1	24.1	28.1
Materials	91	3.1	2 023	59.5	43.4	71.3	53.9	13.8
Real Estate	70	1.9	347	54.9	33.3	67.7	44.3	24.1
Utilities	72	2.7	2 358	57.4	44.2	69.4	55.2	28.1

Examining the regional allocation in Table 7, the largest weight is concentrated in the United States, while Japan and Canada exhibit the highest weighted average carbon intensities[20]. Exposure scores are largely homogeneous across regions for both the 2030 and 2090 horizons, although Japan shows a slightly lower weighted average exposure. Sensitivity scores also display limited dispersion, with Canada recording marginally higher (less favourable) values in both periods. The United States has the highest weighted average green revenue share, whereas the "Others" category records the lowest. Overall, cross-regional differences in exposure and sensitivity are relatively modest. However, aggregation at the

[18] n_j is the number of stocks in sector S_j while b_j is the weight of sector S_j in the benchmark (MSCI World index).

[19] For each metric x, the weighted average for group $\mathcal{G}_j$ is computed as follows:

$$x_j = \frac{\sum_{i \in \mathcal{G}_j} w_i x_i}{\sum_{i \in \mathcal{G}_j} w_i}$$

where group $\mathcal{G}_j$ corresponds to the j^{th} sector (or region) in the sector (or region) analysis.

[20] For each metric x, we use the same approach as above to compute the weighted average for region or country C_k.

macro-regional level may mask important underlying heterogeneity arising from differences in sector composition, market capitalization concentration, and the distribution of physical climate hazards. Moreover, the index is heavily weighted toward U.S. companies, with relatively limited representation from China and other emerging markets. As a result, the analysis may not fully reflect the global diversity of climate-related exposures and risks. This concern is confirmed when the same analysis is performed at a country level (see Table 29 in the Appendix on page 70). We observe differences of more than ten percentage points between stocks in countries with low and high exposure to physical risk. The least exposed stocks are found in New Zealand and Norway, while the most exposed are in Israel and Spain. regarding the sensitivity score, the least sensitive stocks are in Israel and the Netherlands, while the most sensitive are in New Zealand and Portugal.

Table 7: Weighted mean of climate risk measures per region (MSCI World Index, medium scenario)

Region	n_k	b_k	$\mathcal{CI}_{1-3,k}$	$\mathcal{PE}_k^{2030}$	$\mathcal{SE}_k^{2030}$	$\mathcal{PE}_k^{2090}$	$\mathcal{SE}_k^{2090}$	$\mathcal{GI}_k$
Canada	83	3.3	1 947	55.8	28.0	68.7	36.4	8.8
Europe	402	16.0	1 699	57.2	25.0	70.1	33.3	8.2
Japan	180	5.5	2 635	55.1	26.3	67.5	34.9	11.9
USA	546	72.4	982	57.7	23.2	69.7	30.7	17.2
Others	111	2.8	1 740	58.3	26.6	71.1	34.6	5.5

Regression analysis To examine the relationship between the scores and sectoral and regional characteristics, we estimate the following regression model:

$$y_i = \alpha + \sum_{j=1}^{m_j-1} \beta_j D_{i,j} + \sum_{k=1}^{m_k-1} \beta_k D_{i,k} + \varepsilon_i$$

where y_i is the dependent variable for company i (i.e., $\mathcal{CI}_{1-3}$, $\mathcal{PE}$, $\mathcal{SE}$, $\mathcal{GI}$), α_i is the intercept, β_j is the coefficient of sector j, $D_{i,j}$ is the dummy variable for company i and sector j, β_k is the coefficient of region/country k, $D_{i,k}$ is the dummy variable for company i and region/country k, and ε_i is the residual. To avoid multicollinearity, we include only $m_j + m_k - 1$ dummy variables for each categorical predictor, with the omitted category serving as the reference (baseline) group. In our specification, Financials is the reference category for sector, while the United States is the reference category for region/country. The intercept α represents the expected value of the dependent variable for firms in the reference group. Each coefficient β_j (or β_k) measures the expected difference in the dependent variable between category j (or k) and the reference category, holding all other factors constant.

Table 8 shows the results of the linear regression that jointly accounts for regional and sectoral effects. Nearly 50% of the observed variability in the $\mathcal{SE}$ score, more precisely 48.53% for $\mathcal{SE}^{2030}$ and 51.50% for $\mathcal{SE}^{2090}$, is explained by the selected covariates. A closer inspection of Table 9 reveals that this explanatory power is almost entirely driven by sectoral effects. Indeed, the regional variables account for only 1.02% of the variability in $\mathcal{SE}^{2030}$ and 1.37% in $\mathcal{SE}^{2090}$. The estimated coefficients for sector and region dummies are consistently positive and statistically significant at the 1% level, with a few exceptions. Notably, the coefficient for the Europe dummy is close to zero and not statistically significant. This suggests that, compared to the baseline group (Financials/USA), most sector/region combinations generally exhibit a greater sensitivity to climate risk, whereas no significant difference is observed for Europe. By contrast, the proportion of variability in the $\mathcal{PE}$ score

Table 8: Estimates $\hat{\beta}_j$ and $\hat{\beta}_k$ of the regression analysis (MSCI World Index, medium scenario)

Sector	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$	$\mathcal{GI}$
Intercept (Fin/USA)	2 006***	56.96***	69.13***	12.50***	16.30***	−0.85
Communication Services	−1 898***	−0.52	−0.25	8.66***	12.20***	0.50
Consumer Discretionary	−1 431***	−0.49	−0.30	18.54***	24.26***	8.15***
Consumer Staples	−1 508***	−0.90*	−0.52	19.09***	25.16***	2.35
Energy	3 012***	0.07	−1.07**	22.28***	27.57***	7.65**
Health Care	−1 897***	0.25	0.26	14.29***	18.91***	0.80
Industrials	1 225***	−0.32	−0.06	17.22***	22.84***	17.74***
Information Technology	−1 753***	−0.29	−0.06	10.35***	14.12***	12.16***
Materials	−298	2.02***	1.55***	29.26***	35.74***	15.45***
Real Estate	−1 628***	−2.12***	−1.56***	20.72***	27.66***	29.29***
Utilities	158	−0.78	−0.72	28.51***	35.72***	32.84***
Canada	64	−1.13**	0.04	2.44**	3.98***	0.07
Europe	−110	−0.35	0.52**	0.32	1.14	2.90**
Japan	472	−2.64***	−2.42***	1.69**	2.64***	2.07
Others	−236	0.81*	1.83***	3.51***	5.14***	0.81
$\bar{R}_c^2$	12.54%	6.60%	10.91%	48.53%	51.50%	20.04%

explained by the model is relatively low, with an adjusted coefficient of determination $\bar{R}_c^2$ equal to 6.60% for $\mathcal{PE}^{2030}$ and 10.91% for $\mathcal{PE}^{2090}$. Unlike the $\mathcal{SE}$ metric, most of the explanatory power in this case derives from regional effects (see Table 9). Sectoral coefficients are predominantly negative and, in almost all cases, not statistically significant at the 1% level. The only notable exceptions are the Materials and Real Estate sectors. In particular, Materials exhibits a small but significant increase in $\mathcal{PE}$ relative to the baseline category (+2.02 and +1.55 for the 2030 and 2090 scenarios, respectively), while Real Estate shows a similar magnitude of effect in the opposite direction (−2.12 and −1.56 for the 2030 and 2090 scenarios, respectively). With respect to regional variables, the estimated coefficient for Japan is negative and significant at the 1% level, while both the sign and significance of the remaining regional coefficients vary across time horizons. Turning to the transition risk measures, the share of variability explained by the selected covariates is modest (12.54% for $\mathcal{CI}_{1-3}$ and 20.04% for $\mathcal{GI}$). This share is entirely due to sectoral effects. Moreover, in almost all cases, sectoral coefficients are statistically significant at the 1% level for both measures. The main difference between the two metrics is the sign of the estimated coefficients. Most sectors exhibit lower carbon intensity (with the exception of Energy, Industrials, and Utilities) and higher green intensity relative to the baseline category. In contrast, there is no evidence that regional effects differ significantly from zero.

Table 9: Estimates $\hat{\beta}_k$ of the regression analysis using region dummies (MSCI World Index, medium scenario)

Region	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$	$\mathcal{GI}$
Intercept (USA)	1 413***	56.69***	68.97***	27.10***	35.38***	9.70***
Canada	834*	−0.77	0.17	4.56***	6.15***	0.29
Europe	143	−0.24	0.61***	0.43	1.16	1.95
Japan	544*	−2.64***	−2.36***	2.13**	3.29**	1.93
Others	−113	0.74	1.77***	3.66***	5.23***	2.96
$\bar{R}_c^2$	0.19%	4.13%	8.58%	1.02%	1.37%	−0.06%

Overall, these findings suggest that transition risk metrics, *i.e.*, namely $\mathcal{CI}$ and $\mathcal{GI}$, are closely linked to the sector affiliation of companies. This relationship is even stronger for sensitivity (or vulnerability) to physical climate risks. However, exposure to physical risks appears to be primarily driven by geographic location rather than industry sector. Nevertheless, the regional aggregation adopted in this analysis may be too coarse to fully capture the underlying sources of variation in this metric. As previously noted, the MSCI World Index is heavily concentrated in the United States and Europe that are likely exposed to similar climate hazards, while excluding emerging markets that may face substantially different risk profiles. In addition, the regional classification reflects the location of firms' headquarters and may not adequately capture the geographic dispersion of subsidiaries and assets, whose locations are instead taken into account by S&P. For these reasons, we further explore geographic heterogeneity by estimating country-level models, as shown in Tables 30 and 31 in the Appendix. Incorporating country dummies yields the largest improvement for the $\mathcal{PE}$ score. The model including sector and country effects explains 18.58% of the variance in $\mathcal{PE}^{2030}$ and 20.97% in $\mathcal{PE}^{2090}$. Most country-level coefficients are negative and statistically significant at the 1% and 5% levels, while the sectoral results remain consistent with those of the baseline model (with Materials and Real Estate continuing to be the only sectors with significant coefficients). The adjusted $\bar{R}_c^2$ coefficient and estimates for the other metrics are largely unaffected by the inclusion of country variables. Finally, none of the country coefficients for $\mathcal{CI}_{1-3}$ are statistically significant, suggesting an absence of a clear relationship between geographic location and emissions.

The case of EM equities We replicate the same analysis for the MSCI Emerging Markets (EM) Index. All results are reported in the Appendix. Below, we summarize the main findings and key differences compared to the MSCI World Index[21]. The first notable difference concerns the range and distribution of physical risk scores. On average, exposure scores in the MSCI EM Index are higher than those in the MSCI World Index and show greater dispersion within each time horizon and risk scenario. In particular, the quantiles $Q_{75\%}$ and $Q_{95\%}$ are consistently higher across all scenarios, resulting in a more right-skewed distribution. The interquartile range $Q_3 - Q_1$ is approximately 7, compared to about 4 for the MSCI World Index, except for the high emissions scenario in 2090 (Table 39 on page 75). Across all years and scenarios, the average sensitivity-adjusted score exceeds the corresponding MSCI World values by about 10 points, and its dispersion is also slightly larger[22]. Overall, these results suggest that, on average, firms in emerging markets are more exposed and vulnerable to climate hazards than firms in developed markets. Sector-level evidence reinforces this conclusion. As shown in Figures 17 and 18 on page 76, exposure scores within each sector are more dispersed than in the MSCI World Index, with generally higher median values. The Energy sector exhibits both the greatest dispersion and the highest median exposure score (66 versus 57 for the MSCI World Index). The Materials sector also displays a relatively high median value, exceeding that of the corresponding sector in the MSCI World Index. Sensitivity scores show a degree of inter-sector heterogeneity and dispersion similar to the developed-market sample, but at substantially higher levels. Median values are typically about 10 points higher. Consumer Discretionary and Information Technology sectors have comparatively lower sensitivity distributions, while the Health Care sector has higher values.

The Pearson correlation analysis reveals patterns that are broadly consistent with those

[21]For the MSCI EM Index, we do not use the $\mathcal{GI}$ metric, as the underlying data may be inconsistent because several emerging-market countries have not yet adopted a standardized green taxonomy.

[22]Further details are reported in Table 39 and Figures 15 and 16 in the Appendix.

observed for the MSCI World Index[23]. Transition risk metrics are positively and significantly correlated with the $\mathcal{SE}$ score, except when only Scope 3 downstream emissions are considered. The relationship with the $\mathcal{PE}$ score, however, remains weak. Notable differences emerge in the correlations between $\mathcal{PE}$ and $\mathcal{CI}_1$, as well as between $\mathcal{PE}$ and $\mathcal{CI}_3^{\mathrm{up}}$ and $\mathcal{CI}_3^{\mathrm{down}}$. In the latter case, the correlation coefficients are lower than those observed for the MSCI World Index and are not statistical significant. By contrast, the correlation between $\mathcal{PE}$ and $\mathcal{CI}_1$ is substantially higher than the corresponding value for the MSCI World Index and is statistically significant at the 1% level. Correlations involving upstream emissions are not statistically significant for either index. However, the sign differs, it is negative for the MSCI World Index and positive for the MSCI EM Index. One plausible explanation is that Scope 3 upstream emissions (purchased goods and services) reported by firms in developed markets often correspond to Scope 1 emissions of producers located in emerging markets. For the sensitivity score, higher correlation coefficients are observed with all measures of carbon intensity, along with lower p-values, particularly for $\mathcal{CI}_3^{\mathrm{down}}$ and $\mathcal{CI}_{1-3}$. Spearman rank correlations largely confirm these findings[24]. The same differences noted for the Pearson correlations persist for the $\mathcal{PE}$ score. For the $\mathcal{SE}$ score, however, the correlation with $\mathcal{CI}_3^{\mathrm{down}}$ becomes negative and significant at the 1% level. The correlation with $\mathcal{CI}_{1-3}$ is also lower than that observed for the MSCI World Index.

The MSCI World and MSCI EM indexes have a similar sectoral composition in terms of the number of constituents, market capitalization weights, and the distribution of weighted-average carbon intensity across sectors. However, substantial differences emerge for physical risk scores (Table 44 on page 78). Within emerging markets, the Real Estate sector has the highest weighted-average exposure score, whereas it has the lowest value in the MSCI World Index. It is followed by Materials, while Communication Services has the lowest exposure score. All sector-level weighted averages for the sensitivity score are higher than those observed in the MSCI World Index. Communication Services shows the most favorable values (18.9 and 25.6 for the 2030 and 2090 medium scenarios, respectively), followed by Financials (19.9 and 27.2, respectively). One notable difference is Information Technology, whose sensitivity scores in emerging markets are substantially higher than in developed markets. This suggests that IT firms in developing countries may be less prepared to cope with the impacts of extreme weather events. Regarding the regional composition of the MSCI EM Index, China has the largest number of constituents and the second highest market weight after the Others category (Table 45 on page 78). The Middle East has the highest weighted-average carbon intensity, the highest exposure score, and a relatively high sensitivity score. In contrast, Emerging Europe exhibits the lowest exposure and sensitivity.

We also examine the regression results, which reveal both similarities and important differences between the two markets[25]. The estimation results are reported in Tables 47–50 in the Appendix. The model that includes sector and region dummies explains a substantial share of variability in physical risk scores. For the sensitivity score, the explanatory power improves markedly relative to the MSCI World Index, with an adjusted coefficient $\bar{R}_c^2$ equal to about 57%. As in developed markets, this result is primarily driven by sectoral effects, with all sector coefficients being statistically significant at the 1% level. For the exposure score, $\bar{R}_c^2$ equals 33.64% for $\mathcal{PE}^{2030}$ and 31.42% for $\mathcal{PE}^{2090}$, which substantially exceeds the corresponding values for the MSCI World Index (no more than 11%). In this case, regional effects play a dominant role. Most regional coefficients are positive and statistically significant at the 1% and 5% levels, except for EM Europe and the Others category. Sectoral

[23]See Tables 40 and 42 in the Appendix.

[24]See Tables 41 and 43 in the Appendix.

[25]For the MSCI EM Index, the financial sector is the reference sector, while China is the reference category for region and country.

coefficients remain largely not significant, except for Materials and Utilities, which confirms a weak relationship between sector affiliation and exposure to physical climate risk. Results for $\mathcal{CI}_{1-3}$ are consistent with those obtained for the MSCI World Index, indicating a modest association with sector affiliation rather than geographic location. Notably, the transition risk coefficients are small and not statistically significant for India and the Middle East (negative for the latter), while all physical risk coefficients are positive and significant at the 1% level. Introducing country-level dummies substantially improves model performance, particularly for the exposure score. In this specification, the model explains 52.44% and 49.02% of the variability in $\mathcal{PE}^{2030}$ and $\mathcal{PE}^{2090}$, respectively. Country coefficients are statistically significant at the 1% and 5% levels in almost all cases. This indicates pronounced heterogeneity in climate risk exposure across emerging market countries. It also highlights geographic location as a key determinant of physical risk. By contrast, the absence of a systematic relationship between corporate emissions and country location is confirmed. Among countries with a sufficient number of constituents, Taiwan, Saudi Arabia, and India have small, positive but not statistically significant coefficients for the transition risk metrics, while their physical risk coefficients are mostly positive and significant at the 1% level. In contrast, Korea displays statistically significant coefficients across all measures, with negative coefficients for physical risk and a positive coefficient for transition risk. For Brazil, the estimated coefficients are negative for all metrics, but are statistically significant at the 1% level only for physical risk scores.

In summary, the main difference between the MSCI World Index and the MSCI Emerging Markets Index is physical climate risk rather than transition risk. On average, companies in emerging markets appear to be more exposed to climate risks and less prepared to address the effects of climate hazards, making them more vulnerable.

3.1.2 Climate risk integration in equity portfolios

We incorporate physical risk measures into a portfolio optimization framework that builds on established methodologies for managing transition risk and facilitating portfolio decarbonization (see, *e.g.*, Le Guenedal and Roncalli (2022), Barahhou *et al.* (2022) and Bhaugeerutty (2025)). Let w denote the vector of portfolio weights and Σ the covariance matrix of asset returns[26]. The objective is to minimize the tracking error volatility of portfolio w with respect to the equity benchmark b, subject to a constraint on climate risk reduction:

$$\begin{aligned} w^{\star} &= \arg\min \frac{1}{2} (w-b)^{\top} \Sigma (w-b) \\ &\text{s.t.} \quad \left\{ \begin{array}{l} \mathcal{CR}(w) \leq (1-\mathcal{R}) \, \mathcal{CR}(b) \\ w \in \Omega \end{array} \right. \end{aligned} \tag{1}$$

where $\mathcal{CR}(w)$ is the climate risk measure, $\mathcal{R}$ is the targeted reduction rate, and $\Omega = \Omega_1 \cap \Omega_2$ is a set of constraints. In particular, $\Omega_1 = \left\{ w : \mathbf{1}_n^{\top} w = 1, \mathbf{0}_n \leq w \leq \mathbf{1}_n \right\}$ ensures that the resulting portfolio is long-only, while Ω_2 represents additional constraints on sector and regional exposures.

[26] We compute the covariance matrix used in the optimization models as:

$$\Sigma = \sigma_m^2 \beta \beta^{\top} + D$$

where σ_m^2 is the variance of the market portfolio, β is the vector of asset beta coefficients, and $D = \operatorname{diag}\left(\tilde{\sigma}_1^2, \ldots, \tilde{\sigma}_n^2\right)$ is the diagonal matrix, whose elements are the idiosyncratic variances. The coefficients are estimated using the capital asset pricing model, in which the asset return R_i follows the one-factor risk model:

$$R_i - r = \alpha_i + \beta_i (R_m - r) + \varepsilon_i$$

where r is the risk free asset, $R_m \sim \mathcal{N}\left(\mu_m, \sigma_m^2\right)$ is the market return and $\varepsilon_i \sim \mathcal{N}\left(0, \tilde{\sigma}_i^2\right)$ is the asset-specific risk.

Risk analysis In Table 10, we analyze the overlap[27] between the climate-managed portfolios constructed under the constraint on the reduction of the carbon intensity and the physical risk measures. When considering the exposure score, the overlap is low even for small reduction rates. For example, the overlap is 72.1% between the portfolios with $\mathcal{R}_{\mathcal{CI}} = 20\%$ and $\mathcal{R}_{\mathcal{PE}} = 5\%$. In fact, the overlap between portfolios managed using physical exposure risk and the benchmark (corresponding to $\mathcal{R}_{\mathcal{CI}} = 0\%$) is already low. However, this is not the case for portfolios managed using transition risk, where the overlap with the benchmark (corresponding to $\mathcal{R}_{\mathcal{PE}} = 0\%$) remains above 85% for reduction rates below 60%. Therefore, increasing $\mathcal{R}_{\mathcal{CI}}$ has little impact, whereas increasing $\mathcal{R}_{\mathcal{PE}}$ has a significant impact. For example, when $\mathcal{R}_{\mathcal{PE}} = 25\%$, the overlap drops to around 2.5%. When the sensitivity score is used instead as a measure of physical risk, the overlap with carbon-based portfolios is higher, particularly for reduction rates up to 40%. Nevertheless, in both cases we observe a clear pattern. Increasing the reduction rate applied to physical risk measures reduces portfolio overlap more than comparable increases in the reduction rate of carbon intensity. This suggests that physical risk constraints have a stronger effect on portfolio construction than transition risk constraints.

Table 10: Overlap (in %) between transition and physical risk-managed tracking portfolios (MSCI World Index, 2030 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 5\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 15\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 25\%$
	$\mathcal{R} = 0\%$	100.0	70.5	43.3	22.4	10.6	2.3
	$\mathcal{R} = 20\%$	93.3	72.1	44.3	23.0	10.9	2.5
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 40\%$	90.2	71.8	44.5	23.2	11.0	2.5
	$\mathcal{R} = 60\%$	85.3	69.3	43.5	22.9	10.8	2.5
	$\mathcal{R} = 80\%$	72.0	62.8	42.9	23.5	10.9	2.7
		$\mathcal{SE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 40\%$	$\mathcal{R} = 60\%$	$\mathcal{R} = 80\%$
	$\mathcal{R} = 0\%$	100.0	91.0	82.4	65.2	41.6	13.3
	$\mathcal{R} = 20\%$	93.3	90.9	83.1	64.5	41.4	13.4
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 40\%$	90.2	89.2	82.4	64.2	41.5	13.7
	$\mathcal{R} = 60\%$	85.3	85.4	80.1	64.4	42.1	14.3
	$\mathcal{R} = 80\%$	72.0	74.1	72.2	60.6	41.0	15.1

Figure 10 shows the annualized tracking error of the climate-managed portfolios. Under carbon intensity constraints, tracking error volatility is moderate, below 60 basis points. In contrast, imposing constraints on the physical exposure score results in substantially higher tracking error volatility[28]. This tracking risk notably increases with scenario severity and in later decades of the projection horizon, even though the achieved reduction levels remain relatively small. The sensitivity-based portfolio occupies an intermediate position. Its tracking error is higher than average under carbon intensity constraints but lower than that induced by exposure score constraints. Moreover, the tracking errors remain within a similar numerical range across all scenarios, indicating relative robustness to scenario variation. However,

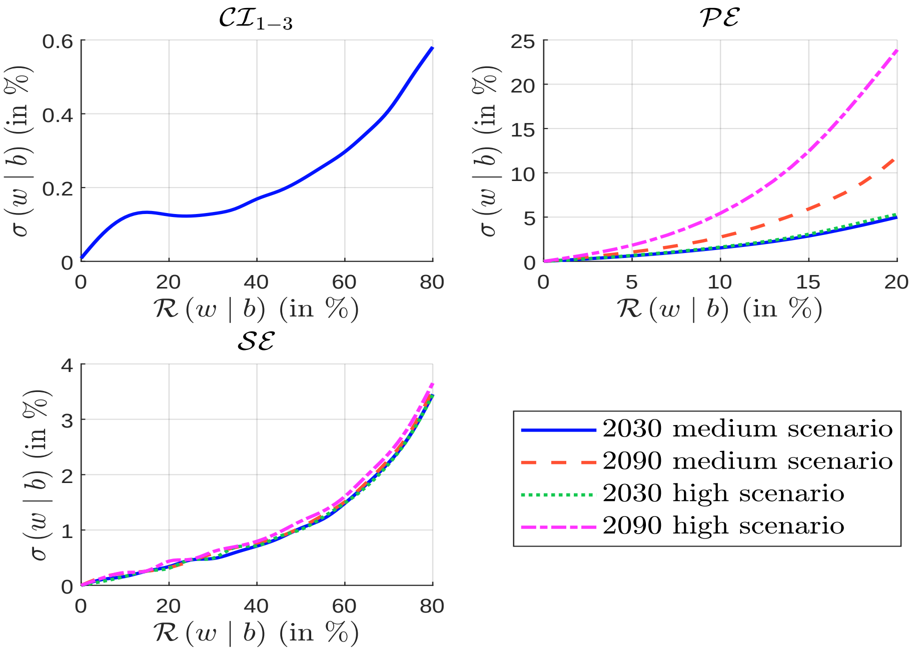
[27] Let w_1 and w_2 be the weight vectors of two portfolios. The overlap between the two portfolios is defined as follows:

$$\text{overlap}\left(w_1, w_2\right) = \sum_{i=1}^{n} \min\left(w_{1,i}, w_{2,i}\right)$$

where $\text{overlap}\left(w_1, w_2\right) \in [0, 1]$. It is equal to 0% if the two portfolios have no assets in common, while it is equal to 100% if the two portfolios are identical.

[28] Reaching up to 25% in some cases.

Figure 10: Tracking error volatility of climate-managed portfolios (MSCI World Index)



targeting a reduction above 40% seems unrealistic from a professional perspective because it generates tracking error volatility that exceeds the commonly accepted threshold of 200 basis points for institutional investors. Overall, these findings suggest that managing portfolios under physical risk constraints is more costly than managing portfolios under transition risk constraints. This is reflected by higher active risk and greater implementation costs for investors seeking to track benchmark performance.

Table 11: Number of invested stocks (MSCI World Index)

$\mathcal{R}$	$\mathcal{CI}$	$\mathcal{PE}$				$\mathcal{SE}$			
		Medium		High		Medium		High	
		2030	2090	2030	2090	2030	2090	2030	2090
0%	1 322	1 322	1 322	1 322	1 322	1 322	1 322	1 322	1 322
5%	1 322	1 314	1 322	1 310	1 299	1 322	1 322	1 322	1 322
10%	1 322	1 208	256	800	78	1 322	1 322	1 322	1 322
15%	1 322	163	54	161	18	1 322	1 322	1 322	1 322
20%	1 322	146	13	59	8	1 322	1 322	1 322	1 322
25%	1 322	32	5	21		1 322	1 322	1 322	1 322
40%	1 322					1 059	1 320	1 045	801
60%	1 288					506	238	523	216
80%	1 262					105	130	111	87

The previous findings are confirmed by the analysis of the number of invested stocks (Table 11) and by the correlation analysis[29]. In the case of physical exposure risk, the composition of the portfolio becomes unrealistic very quickly when $\mathcal{R}_{\mathcal{PE}} \geq 10\%$. For example, the portfolio contains less than 200 stocks when $\mathcal{R}_{\mathcal{PE}} = 15\%$, and only 18 stocks under the 2090 high scenario. This occurs despite the fact that portfolio optimization is performed

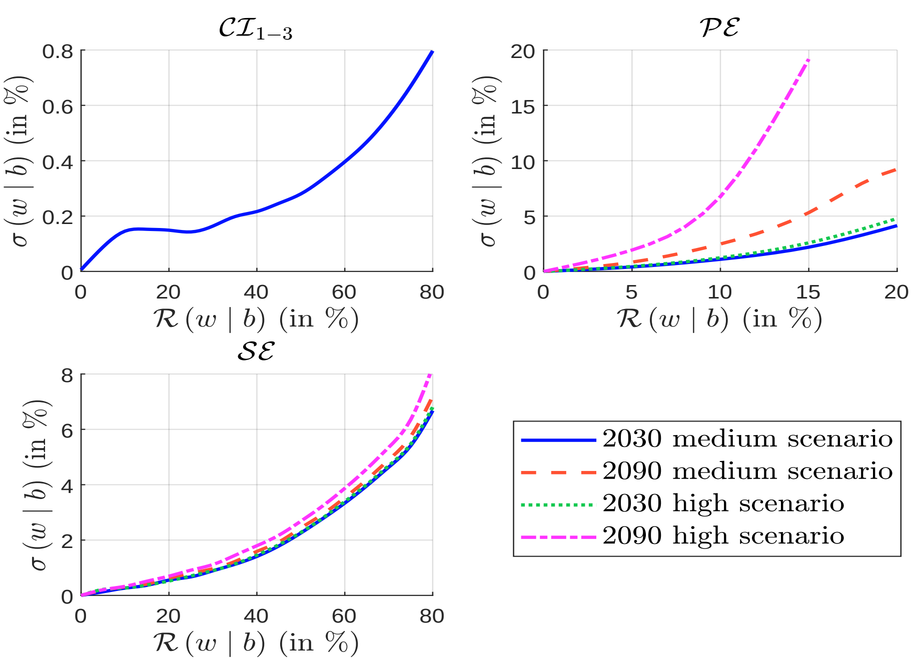
[29]See Tables 33 and 34 on page 73.

under a long-only constraint. In practice, portfolio construction typically includes additional constraints, such as sector limits and weight bounds (Barahhou *et al.*, 2022; Ben Slimane *et al.*, 2023). Therefore, reducing physical exposure risk is practically infeasible when considering a realistic portfolio optimization framework. This result is not surprising since physical risk is largely systemic, and systemic risks are difficult — if not impossible — to diversify. By contrast, vulnerability risk varies significantly across sectors and across firms, even when companies face the same hazards and are located in the same geographical areas. Therefore, investors should primarily focus on managing physical vulnerability risk rather than physical exposure risk.

Table 12: Overlap (in %) between transition and physical risk-managed tracking portfolios (MSCI EM Index, 2030 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=5\%$	$\mathcal{R}=10\%$	$\mathcal{R}=15\%$	$\mathcal{R}=20\%$	$\mathcal{R}=25\%$
	$\mathcal{R}=0\%$	100.0	81.5	61.5	40.4	23.5	10.4
	$\mathcal{R}=20\%$	92.1	82.1	63.3	40.5	23.6	10.3
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	93.2	81.5	62.4	40.3	23.5	10.2
	$\mathcal{R}=60\%$	83.0	77.7	60.5	39.7	22.9	9.5
	$\mathcal{R}=80\%$	66.3	64.7	54.9	38.5	22.2	8.9
		$\mathcal{SE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=10\%$	$\mathcal{R}=20\%$	$\mathcal{R}=40\%$	$\mathcal{R}=60\%$	$\mathcal{R}=80\%$
	$\mathcal{R}=0\%$	100.0	88.0	77.0	50.8	25.5	8.8
	$\mathcal{R}=20\%$	92.1	88.4	77.0	50.5	25.3	8.5
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	93.2	87.5	76.7	50.4	25.4	8.7
	$\mathcal{R}=60\%$	83.0	80.2	71.6	48.5	25.3	9.2
	$\mathcal{R}=80\%$	66.3	64.9	60.8	43.8	25.5	10.0

Figure 11: Tracking error volatility of climate-managed portfolios (MSCI EM Index)



The same qualitative patterns are observed for the MSCI EM Index as for the MSCI World Index. However, the overlap associated with exposure scores is higher for the MSCI EM Index than for the MSCI World Index, with a difference of around 10–20 percentage points across all levels of $\mathcal{R}$. Conversely, the overlap associated with sensitivity scores is lower. Regarding tracking error volatility, similar patterns emerge for physical exposure risk across the MSCI EM and MSCI World indices. However, tracking error volatility is higher when sensitivity scores are considered. These findings suggest that managing physical exposure risk poses an equal challenge in both developed and emerging markets, whereas managing vulnerability risk is more difficult in the latter. Overall, these results are consistent with the academic literature on physical risk and adaptation (Roncalli, 2026).

Sector allocation In Table 13, we report the sector allocation obtained when imposing a constraint on total carbon intensity. The results suggest that a decarbonized portfolio corresponds to a strategy that is long on Information Technology, Health Care, and Communication Services, and short on Energy, Financials, and Utilities. These findings are broadly consistent with previous studies (Le Guenedal and Roncalli, 2022; Barahhou *et al.*, 2022; Ben Slimane *et al.*, 2023), with the notable exception of the Financials sector. This difference arises from the difficulty of accurately measuring Scope 3 emissions for financial institutions. For a long time, Scope 3 downstream emissions were substantially underestimated due to simplistic measurement approaches. More recently, ESG rating agencies have made significant progress in assessing these emissions for the Financials sector, including indirect emissions associated with lending, mortgages, and financing activities in carbon-intensive industries. As a result, earlier studies suggesting that portfolio decarbonization corresponds to a long position on Financials often relied solely on Scopes 1, 2 and 3 upstream emissions, or were affected by severe underestimation of Scope 3 downstream emissions.

Table 13: Sector allocation (in %) with constraints on $\mathcal{CI}_{1-3}$ (MSCI World Index)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Communication Services	8.67	8.85	8.92	9.24	9.94	11.40
Consumer Discretionary	9.93	10.14	10.25	10.57	10.90	11.16
Consumer Staples	5.46	5.43	5.49	5.70	5.78	4.87
Energy	3.53	3.20	3.03	2.45	1.45	0.23
Financials	16.40	15.51	15.68	15.21	14.87	12.28
Health Care	9.97	9.69	9.96	10.44	11.89	14.27
Industrials	10.94	11.22	10.69	9.76	8.05	7.08
Information Technology	27.39	27.53	27.74	28.42	29.76	32.00
Materials	3.12	3.41	3.33	3.21	2.69	1.96
Real Estate	1.88	2.38	2.39	2.74	3.11	3.85
Utilities	2.70	2.64	2.52	2.26	1.56	0.90

Tables 14 and 15 show the sector allocations obtained by imposing constraints on physical exposure and sensitivity scores, respectively. The resulting strategy for managing physical exposure risk involves being long on Energy, Financials, Utilities, and Real Estate, and short on Communication Services, Consumer Discretionary, and Information Technology. This pattern is the opposite of that observed under a carbon intensity constraint. Increasing the reference time horizon or the severity of the climate scenario further increases allocations to the Energy sector and reduces allocations to Industrials and Information Technology. When the constraint targets physical sensitivity risk, the portfolio predominantly tilts toward Financials and underweights all other sectors. At higher reduction rates, this tilt toward Financials persists across all reference decades and scenarios. This reflects the

Table 14: Sector allocation (in %) with constraints on $\mathcal{PE}$ (MSCI World Index, 2030 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Communication Services	8.67	8.80	7.36	2.83	0.11	0.00
Consumer Discretionary	9.93	9.96	8.94	7.12	2.54	0.10
Consumer Staples	5.46	4.62	4.91	4.86	5.29	3.46
Energy	3.53	3.77	5.44	8.43	14.46	21.92
Financials	16.40	16.15	16.42	20.23	22.07	28.32
Health Care	9.97	6.34	3.34	3.23	4.81	4.30
Industrials	10.94	11.07	9.71	8.68	8.07	2.65
Information Technology	27.39	26.86	23.80	17.52	10.48	5.30
Materials	3.12	3.00	4.01	4.57	4.81	4.28
Real Estate	1.88	4.36	6.56	8.81	11.20	9.51
Utilities	2.70	5.08	9.51	13.72	16.17	20.15

Table 15: Sector allocation (in %) with constraints on $\mathcal{SE}$ (MSCI World Index, 2030 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Communication Services	8.67	9.08	9.25	9.01	6.62	1.69
Consumer Discretionary	9.93	9.16	8.31	6.67	4.10	0.24
Consumer Staples	5.46	4.90	3.94	1.78	0.44	0.00
Energy	3.53	2.76	2.10	0.65	0.03	0.00
Financials	16.40	21.38	27.55	42.46	60.35	83.67
Health Care	9.97	9.78	9.22	7.72	3.49	0.64
Industrials	10.94	10.06	8.46	3.92	1.94	4.09
Information Technology	27.39	27.67	27.72	27.11	22.91	9.67
Materials	3.12	2.05	1.16	0.11	0.04	0.00
Real Estate	1.88	1.66	1.31	0.46	0.05	0.00
Utilities	2.70	1.50	0.97	0.12	0.03	0.00

systematically lower sensitivity scores of the Financial sector[30]. Consequently, the sector composition of the optimized portfolio differs substantially from that of the benchmark and diverges significantly from the index, potentially altering sectoral risk exposures. A consistent pattern emerges across both physical risk measures. The Information Technology sector experiences a significant decrease in portfolio weight. This behavior is not observed in portfolios constructed under carbon intensity constraints.

When we compare the MSCI EM Index and the MSCI World Index, we notice both similarities and significant differences[31]. Under a carbon intensity reduction constraint, the two markets have comparable sector allocations. However, portfolio strategies that explicitly incorporate physical risk lead to significant differences in sector weights. When portfolios are optimized using the exposure score, the sector allocations change markedly. In this case, the strategy becomes long on Health Care and Industrials and short on Financials and Real

[30] The comparatively low vulnerability risk scores of the Financials sector reflect the immaterial nature of its business model, which is characterized by an absence of direct production facilities, a flexible geographic footprint, and limited exposure to physical supply chains. Unlike sectors that rely on physical infrastructure or engage in climate-sensitive operations, financial institutions primarily perform office-based activities and therefore face minimal direct exposure to climate hazards such as floods, heat stress, and extreme weather events. However, this characterization may understate the vulnerability of the sector because it does not take into account the indirect exposure from loan portfolios, underwriting activities, and investments in climate-exposed assets. Consequently, current physical risk metrics primarily capture direct operational risks, and not indirect systemic physical risks.

[31] The results for the MSCI EM Index are given in Tables 55, 56 and 57 on page 83.

Estate. Energy exposure increases considerably less in emerging markets than in developed markets. In the MSCI EM Index, Energy exposure rises from 3.92% to 11.53%, compared to an increase from 3.53% to 21.92% in the MSCI World Index. Information technology exhibits the same directional trend in both indices but shows a more limited reduction in emerging markets at higher values of the reduction parameter $\mathcal{R}$. In emerging markets, more severe risk scenarios and longer time horizons lead to a significant increase in Industrials, accompanied by the near-complete elimination of Information Technology exposure. Under constraints on the sensitivity score, sector allocations are generally similar across markets, with the most substantial reductions concentrated in Financials. However, notable divergences emerge for Communication Services and Information Technology. The weight of Communication Services nearly doubles at $\mathcal{R} = 80\%$, consistent with its relatively lower vulnerability among EM firms. By contrast, the weights of Information Technology decline sharply as $\mathcal{R}$ increases, reaching zero at the highest reduction rate. This pattern suggests that IT firms in emerging markets are more physically vulnerable than their counterparts in developed markets. Several factors may explain these differences, most notably variations in supply chain organization. For instance, IT firms in developed markets frequently depend on suppliers and production facilities in developing countries. Consequently, the physical vulnerability of IT firms in the MSCI World Index may be underestimated if indirect exposure through global supply chains is not taken into account. These contrasting dynamics persist across climate scenarios and reference decades.

Table 16: Regional allocation (in %) with constraints on $\boldsymbol{\mathcal{CI}}_{1-3}$ (MSCI World Index)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Canada	3.31	3.34	3.29	3.14	2.87	3.08
Europe	16.04	17.38	17.11	17.17	16.36	16.40
Japan	5.45	6.20	5.98	6.07	5.58	5.36
USA	72.38	69.59	70.26	70.24	72.28	71.83
Others	2.82	3.48	3.35	3.39	2.91	3.32

Table 17: Regional allocation (in %) with constraints on $\boldsymbol{\mathcal{PE}}$ (MSCI World Index, 2030 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Canada	3.31	7.33	12.79	16.46	13.39	10.09
Europe	16.04	16.96	19.59	22.48	26.39	29.08
Japan	5.45	7.93	6.46	2.66	0.68	0.00
USA	72.38	64.61	57.00	52.49	49.54	46.42
Others	2.82	3.17	4.15	5.90	10.01	14.40

Regional allocation Tables 16–18 report the regional allocations of the risk-managed portfolios. When the carbon intensity constraint is imposed, the regional weights generally align with those of the benchmark index. However, incorporating physical risk measures results in noticeable shifts in geographic allocation. When the exposure score is constrained, portfolio weights shift toward Europe and the Others category, while allocation to the United States declines substantially. For the remaining regions, the response to increasing reduction rates is not strictly linear. As the reference time horizon increases, and under the high severity scenario, the U.S. portfolio share decreases more sharply, accompanied by a corresponding increase in European exposure. This pattern indicates a geographic rebalancing in favor of European equities. Applying a constraint on the sensitivity score also results in meaningful deviations from the benchmark regional weights. In this case, allocation to Europe rises significantly, and the U.S. share declines. This reallocation pattern persists across alternative scenarios. The reduction in the relative weight of the United States under physical risk constraints is closely linked to the decline in exposure to the information technology sector, which is a substantial component of the U.S. equity market.

Table 18: Regional allocation (in %) with constraints on $\boldsymbol{\mathcal{SE}}$ (MSCI World Index, 2030 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Canada	3.31	3.49	3.92	5.04	5.49	6.61
Europe	16.04	17.53	18.71	19.51	21.86	32.96
Japan	5.45	5.71	5.63	4.33	2.40	0.83
USA	72.38	70.03	68.08	66.98	65.77	55.91
Others	2.82	3.24	3.65	4.14	4.48	3.68

When the MSCI EM portfolio is constrained to reduce total carbon intensity, its regional weights remain closely aligned with those of the benchmark[32]. This indicates a weak relationship between carbon intensity and geographic location. The resulting adjustments are modest, consisting mainly of a slight increase in the weight of China and a minor reduction in the weight of EM Europe. In contrast, portfolios optimized using the physical exposure score significantly deviate from the benchmark's regional allocations (Table 61 on page 85). Allocations to Africa, India, and the Middle East decline substantially, with the reallocated weight primarily directed toward EM Europe and the Others category. The weight of China also increases as physical exposure decreases. These reallocations become more pronounced under high severity scenarios and over longer time horizons. Constraints based on the sensitivity score produce regional allocation changes that are largely nonlinear (Table 62 on page 85). This suggests that geographic location is not the dominant driver of vulnerability to physical climate risk. As the reduction parameter $\mathcal{R}$ increases, the only consistent monotonic patterns observed are an increase in allocation to Africa and a decrease in allocation to the Middle East. These dynamics remain consistent across climate scenarios and reference decades.

3.2 Strategic asset allocation

We examine a strategic asset allocation exercise that aims to address climate-related physical risks across countries and regions. Our analysis focuses on twenty countries: Australia, Brazil, Canada, China, France, Germany, India, Italy, Japan, South Korea, Mexico, the Netherlands, Poland, South Africa, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States. First, we assess the physical climate risk of these countries using data from the ND-GAIN database. Specifically, we examine differences in the key dimensions of physical climate risk: exposure, sensitivity, adaptation, vulnerability, and readiness. The second section illustrates how managing climate-related physical risk affects strategic asset allocation decisions.

3.2.1 ND-GAIN country index

The ND-GAIN (Notre Dame Global Adaptation Initiative) database is a widely used source of country-level indicators related to climate change vulnerability and readiness. Developed

[32]See Table 60 on page 83.

by the University of Notre Dame, the database provides annual rankings for 185 countries based on 45 indicators from 1995 to the present (last year available is 2023). The ND-GAIN country index consists of two components:

1. Vulnerability, which measures the physical vulnerability risk of the country. It is a composite metric composed of exposure, sensitivity, and adaptive capacity scores, and is aggregated across six life-supporting sectors: ecosystem services, food, health, human habitat, infrastructure, and water. The vulnerability score is normalized to range from 0 to 1, with higher scores indicating greater vulnerability (worse conditions).

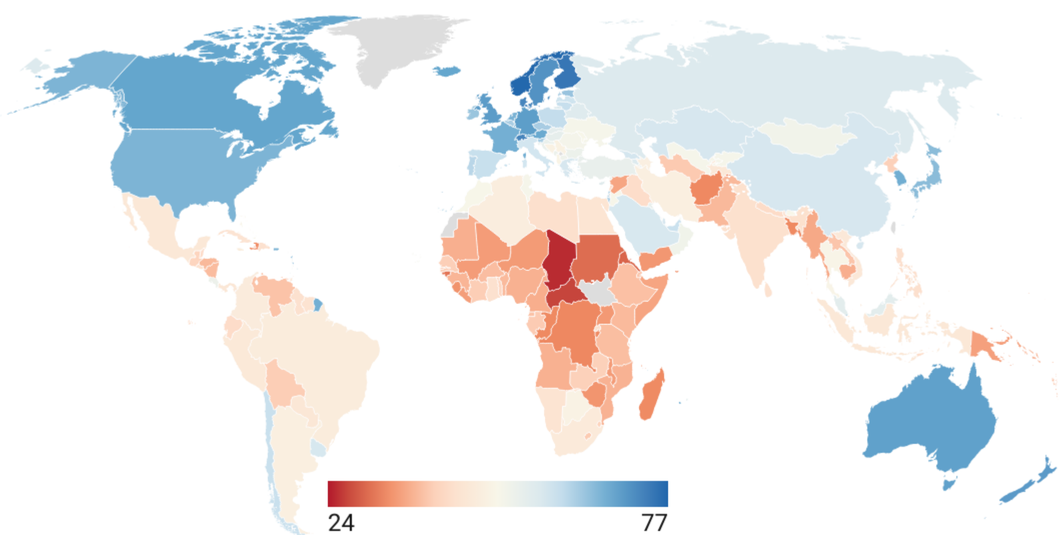
2. Readiness, which represents the ability of a country to leverage investments and convert them into effective adaptation actions. It considers the economic, governance, and social dimensions. The readiness score is normalized to range from 0 to 1, with higher scores indicating greater readiness (better conditions).

The synthetic ND-GAIN score is then obtained by combining the two components in the following way:

$$\text{ND-GAIN score} = 50 \times (\text{Readiness score} - \text{Vulnerability score} + 1)$$

The ND-GAIN score ranges from 0 to 100. It provides an aggregate measure of a country's overall climate adaptation potential, but it is not a direct measure of physical climate risk. In contrast, the vulnerability component reflects physical risk, because it incorporates indicators of exposure and sensitivity to climate-related hazards.

Figure 12: ND-GAIN country score (2023)



Source: ND-GAIN (2025) & Authors' calculations (created by Datawrapper).

Figure 12 shows the global distribution of the composite ND-GAIN country scores. The geographic pattern is clear, the top ten countries are in developed countries, while the bottom ten countries are concentrated in Africa and emerging markets (namely, Chad, the Central African Republic, Eritrea, Sudan, Guinea-Bissau, Congo-Kinshasa, Afghanistan, Congo-Brazzaville, Bangladesh, and Burundi). This pattern underscores how climate risks intersect with development levels. Countries that are least responsible for climate change often face the greatest impacts while possessing the fewest resources to adapt (Roncalli, 2026).

Because the ND-GAIN country index is a composite indicator, it is informative to examine the relationships among its underlying components[33]. Table 19 reports the correlation matrix for the individual scores: exposure, sensitivity, adaptive capacity (or adaptation), vulnerability, readiness, and the overall ND-GAIN index. As expected, vulnerability and readiness are strongly negatively correlated (−63.7%), indicating that more vulnerable countries tend to be less prepared to cope with climate-related events. Focusing on the vulnerability dimension, its three components (exposure, sensitivity, and adaptive capacity) are all positively correlated. This implies that countries facing lower exposure to climate hazards also tend to be less sensitive and to possess greater adaptive capacity. The strongest association is observed between sensitivity and capacity (approximately 60%), while correlations involving exposure are more moderate (25.3% with sensitivity and 46.3% with capacity). These differences are intuitive. Exposure largely reflects region-specific and systemic physical risk factors, whereas sensitivity and adaptive capacity are more country-specific and reflect structural and policy-related characteristics. While countries have limited ability to influence their exposure to climate hazards, they can actively manage sensitivity and adaptive capacity, for example through targeted investments and adaptation policies. An additional insight emerges from the dispersion of the different scores. The standard deviations of exposure, sensitivity, capacity, vulnerability, readiness, and ND-GAIN are 8.1%, 8.7%, 16.5%, 9.2%, 15.4%, and 11.15, respectively. Adaptive capacity and readiness are thus the most heterogeneous dimensions, indicating substantial cross-country variation. This greater dispersion helps explain the very high correlation between capacity and vulnerability (91.2%). Because adaptive capacity varies more widely across countries than exposure or sensitivity, it had a larger contribution to the overall vulnerability score.

Table 19: Correlation matrix of physical risk scores (2023, ND-GAIN)

	Exposure	Sensitivity	Capacity	Vulnerability	Readiness	ND-GAIN
Exposure	100.0%	25.3%	46.3%	67.9%	−26.7%	−44.8%
Sensitivity	25.3%	100.0%	59.3%	75.8%	−46.5%	−62.1%
Capacity	46.3%	59.3%	100.0%	91.2%	−78.4%	−90.5%
Vulnerability	67.9%	75.8%	91.2%	100.0%	−63.7%	−85.0%
Readiness	−26.7%	−46.5%	−78.4%	−63.7%	100.0%	94.8%
ND-GAIN	−44.8%	−62.1%	−90.5%	−85.0%	94.8%	100.0%

Table 20 shows the physical risk scores for the selected countries. In terms of exposure risk, eight of the ten countries with the lowest exposure are European. Switzerland has the lowest exposure in the sample. Italy stands out as an outlier within Europe, displaying relatively high exposure. By contrast, emerging economies are concentrated at the upper end of the exposure distribution, with Japan and India displaying particularly high levels. A different pattern emerges for sensitivity. The least sensitive countries are predominantly non-European and include Canada, Australia, Mexico, the United States and Brazil. Notably, Japan and the Netherlands are the two countries with the highest sensitivity in the sample.

[33] The interpretation of the ND-GAIN scores is as follows. Higher values of exposure, sensitivity, capacity, and vulnerability indicate greater physical climate risk, whereas higher values of readiness and the overall ND-GAIN index correspond to lower physical risk. Accordingly, the direction of these metrics differs across dimensions. In particular, a lower score for adaptive capacity reflects stronger adaptation capabilities and thus lower physical risk.

Table 20: Physical risk scores by country (2023, ND-GAIN)

Exposure		Sensitivity		Capacity		Vulnerability		Readiness		ND-GAIN	
Switzerland	0.309	Canada	0.154	Netherlands	0.200	Switzerland	0.251	Sweden	0.739	Switzerland	72.894
Poland	0.334	Australia	0.161	Switzerland	0.220	Canada	0.282	Switzerland	0.709	Sweden	71.096
Germany	0.347	Mexico	0.197	UK	0.247	UK	0.288	Korea	0.705	UK	69.854
Spain	0.361	USA	0.203	Spain	0.251	Germany	0.301	Australia	0.700	Germany	69.612
UK	0.390	Brazil	0.205	USA	0.252	France	0.304	Germany	0.694	Australia	69.197
France	0.397	Sweden	0.221	Japan	0.255	Spain	0.305	Netherlands	0.687	Canada	68.549
Netherlands	0.397	UK	0.227	Germany	0.255	Poland	0.306	UK	0.685	Korea	67.406
Sweden	0.410	Switzerland	0.227	France	0.256	USA	0.312	Japan	0.677	France	67.200
Turkey	0.415	South Africa	0.231	Canada	0.258	Australia	0.316	Canada	0.653	Netherlands	66.660
South Africa	0.431	Poland	0.246	Italy	0.281	Sweden	0.317	France	0.648	USA	66.451
Canada	0.433	France	0.259	Korea	0.293	Italy	0.342	USA	0.641	Japan	65.381
Italy	0.441	China	0.265	Australia	0.309	Netherlands	0.354	China	0.544	Poland	60.461
China	0.448	Turkey	0.276	Sweden	0.318	Korea	0.357	Italy	0.518	Spain	60.084
Australia	0.480	Korea	0.283	Poland	0.337	Brazil	0.369	Poland	0.515	Italy	58.802
USA	0.481	Spain	0.298	China	0.424	Japan	0.369	Spain	0.506	China	58.102
Mexico	0.487	Italy	0.304	Brazil	0.425	Turkey	0.375	Turkey	0.453	Turkey	53.903
Korea	0.494	Germany	0.308	Turkey	0.439	China	0.382	India	0.355	Brazil	47.156
Brazil	0.501	India	0.324	Mexico	0.475	Mexico	0.387	South Africa	0.327	South Africa	46.598
Japan	0.520	Japan	0.333	South Africa	0.539	South Africa	0.395	Brazil	0.312	Mexico	45.775
India	0.572	Netherlands	0.465	India	0.562	India	0.485	Mexico	0.302	India	43.534

Source: ND-GAIN (2025).

In terms of adaptive capacity, the Netherlands emerges as the top performer. Several other European countries, along with the United States, Japan and Canada, also rank highly in this respect. In contrast, Poland and Sweden exhibit comparatively lower adaptive capacity than other European countries, while emerging economies generally display weaker adaptive capacity. Regarding vulnerability, Switzerland, Canada and the United Kingdom are the least vulnerable, while emerging economies and Japan are among the most vulnerable. Regarding readiness, most European countries are at the higher end of the scale, with notable exceptions including Italy, Spain and Poland. Emerging markets generally exhibit lower levels of readiness. However, Korea displays high levels of readiness, and Japan also performs relatively well on this metric despite its elevated exposure. The composite ND-GAIN index incorporates these patterns. DM economies achieve the highest overall scores, while EM regions rank the lowest. Notably, Korea is an outlier in this regard. Its moderate vulnerability is offset by its comparatively strong adaptive capacity and readiness. Overall, the results highlight a clear distinction between developed and emerging economies. Developed-market countries tend to combine lower vulnerability with stronger adaptive capacity and readiness, resulting in superior ND-GAIN outcomes. In contrast, emerging-market economies face higher exposure and vulnerability alongside weaker capacity and readiness. These findings suggest that investments and policies aimed at strengthening adaptive capacity and readiness could significantly reduce climate vulnerability, even in contexts where exposure remains high, as demonstrated by Korea and Japan.

3.2.2 Impact of physical risk on regional allocation

We consider a strategic asset allocation exercise with the twenty selected countries. We form 4 buckets:

- Europe: France, Germany, Italy, the Netherlands, Poland, Spain, Sweden, Switzerland, and United Kingdom;
- USA: United States;
- Other developed markets: Australia, Canada and Japan;
- Emerging markets: Brazil, China, India, Korea, Mexico, South Africa, and Turkey.

We consider six different strategic asset allocations, and we report below the corresponding benchmark portfolio b:

Benchmark	Investor profile	Policy	Europe	USA	Other DM	EM	Europe	USA	Other DM	EM
			Equity				Bond			
#1	European/balanced	60/40	30%	15%	5%	10%	30%	10%	0%	0%
#2	European/aggressive	80/20	40%	20%	10%	10%	15%	5%	0%	0%
#3	American/balanced	60/40	10%	40%	5%	5%	5%	30%	5%	0%
#4	American/aggressive	80/20	5%	60%	5%	10%	3%	15%	2%	0%
#5	Global/balanced	60/40	10%	20%	10%	20%	10%	10%	10%	10%
#6	Global/aggressive	80/20	15%	30%	10%	25%	5%	5%	5%	5%

Within each asset bucket and asset class (equities and bonds), we assume that allocations are weighted by the market value of assets in each country. As a result, each bucket portfolio

Table 21: Estimation of the maximum reduction rate $\mathcal{R}^+$ of physical risk

Portfolio	Exposure	Sensitivity	Capacity	Vulnerability	Readiness	ND-GAIN
European/balanced	27.40%	32.7%	27.20%	21.1%	18.3%	11.6%
European/aggressive	28.00%	36.1%	27.10%	21.2%	17.0%	11.1%
American/balanced	34.20%	31.8%	23.40%	21.2%	16.0%	10.6%
American/aggressive	35.20%	30.5%	26.90%	22.3%	18.0%	11.9%
Global/balanced	34.20%	39.8%	36.50%	27.4%	23.7%	16.5%
Global/aggressive	34.20%	38.6%	36.40%	27.0%	23.8%	16.4%

can be interpreted as a market portfolio. We then consider two approaches for incorporating physical risk into strategic asset allocation. For that, we adopt a standard mean-variance optimization framework:

$$\begin{aligned} w^\star &= \arg\min \frac{1}{2} w^\top \Sigma w - \gamma w^\top \pi \\ &\text{s.t.} \quad \left\{ \begin{array}{l} \boldsymbol{\mathcal{PR}}(w) \leq (1 - \mathcal{R}) \, \boldsymbol{\mathcal{PR}}(b) \\ w \in \Omega \end{array} \right. \end{aligned} \tag{2}$$

where Σ is the asset covariance matrix, π is the vector of risk premia, γ is the coefficient of risk tolerance, and $\boldsymbol{\mathcal{PR}}(w)$ is the physical risk measure, $\mathcal{R}$ is the targeted reduction rate of physical risk, and $\Omega = \Omega_1 \cap \Omega_2$ is a set of constraints. In particular, $\Omega_1 = \left\{ w : \mathbf{1}_n^\top w = 1, \mathbf{0}_n \leq w \leq \mathbf{1}_n \right\}$ ensures that the resulting portfolio is long-only, while Ω_2 represents additional constraints. In particular, we impose asset-class neutrality between equities and bonds, requiring the portfolio w to maintain the same equity-bond allocation as the benchmark portfolio b. In the first approach, we assume that the benchmark portfolio is optimal[34], meaning that $\pi = \gamma^{-1} \Sigma b$. This implies that the optimization objective reduces to a tracking-error framework:

$$\begin{aligned} w^\star &= \arg\min \frac{1}{2} w^\top \Sigma w - w^\top \Sigma b \\ &\text{s.t.} \quad \left\{ \begin{array}{l} \boldsymbol{\mathcal{PR}}(w) \leq (1 - \mathcal{R}) \, \boldsymbol{\mathcal{PR}}(b) \\ w \in \Omega \end{array} \right. \end{aligned} \tag{3}$$

We solve this optimization problem for each of the six benchmark portfolios and six alternative physical risk scores. For each case, we determine the maximum feasible reduction rate $\mathcal{R}^+$ such that the constraint set remains non-empty. The resulting estimates of $\mathcal{R}^+$ are reported in Table 21. The results show that the attainable reduction rate depends strongly on the choice of physical risk metric. In particular, reducing the composite ND-GAIN score is more challenging than reducing exposure or sensitivity alone. This reflects the fact that sensitivity (and readiness) exhibit the greatest cross-sectional dispersion across countries. However, readiness appears to be the second most difficult dimension to improve. One plausible explanation is that the sample of countries consists primarily of large economies, which generally have greater fiscal capacity and institutional resources to prepare for and adapt to physical risks. Finally, an analysis of the resulting portfolio compositions shows that achieving a reduction rate above approximately 10% is generally unrealistic because it results in highly concentrated portfolios and binding constraints.

[34]From the first order condition $\frac{1}{2}(2\Sigma w^\star) - \gamma\pi = \mathbf{0}_n$, we deduce that $\pi = \gamma^{-1}\Sigma w^\star$.

Table 22: Portfolio allocation changes relative to the benchmark under a 10% physical risk reduction

Investor	Asset class	Exposure	Sensitivity	Capacity	Vulnerability	Readiness	ND-GAIN	Exposure	Sensitivity	Capacity	Vulnerability	Readiness	ND-GAIN
		Balanced						Aggressive					
European	Europe equity	5.9	−1.0	3.2	7.2	5.3	21.4	10.2	−1.5	3.7	8.5	8.3	32.7
	USA equity	−1.2	−0.2	0.1	−2.0	0.7	−12.8	−2.9	−0.1	0.2	−1.9	−0.4	−20.0
	Other DM equity	−2.3	2.3	0.9	1.4	0.1	1.1	−3.9	2.9	1.1	−0.2	−2.7	−2.7
	EM equity	−2.5	−1.0	−4.2	−6.7	−6.0	−9.7	−3.4	−1.3	−5.1	−6.3	−5.1	−10.0
	Europe bond	10.0	−4.2	0.3	4.9	6.6	10.0	5.0	−4.6	1.1	5.0	5.0	5.0
	USA bond	−10.0	4.2	−0.3	−4.9	−6.6	−10.0	−5.0	4.6	−1.1	−5.0	−5.0	−5.0
American	Europe equity	5.1	−0.9	3.3	5.5	13.6	43.2	7.2	−1.0	4.2	8.8	24.4	55.7
	USA equity	−1.3	0.4	1.4	−0.5	−9.5	−33.2	−1.5	0.2	1.3	−3.0	−16.9	−40.7
	Other DM equity	−2.3	1.9	−0.2	−0.7	−5.0	−5.0	−2.4	3.6	1.4	2.6	−4.6	−5.0
	EM equity	−1.5	−1.4	−4.5	−4.3	0.9	−5.0	−3.3	−2.8	−6.9	−8.4	−2.8	−10.0
	Europe bond	18.5	−4.2	16.0	12.4	35.0	35.0	17.0	−3.0	6.7	13.0	17.0	17.0
	USA bond	−13.8	−0.0	−11.0	−21.5	−30.0	−30.0	−15.0	−4.9	−4.7	−15.0	−15.0	−15.0
	Other DM bond	−4.7	4.2	−5.0	9.2	−5.0	−5.0	−2.0	7.9	−2.0	2.0	−2.0	−2.0
Global	Europe equity	4.4	−0.8	2.3	5.2	4.2	8.8	8.4	−1.1	3.4	7.4	5.6	11.0
	USA equity	−1.4	0.5	0.5	0.1	0.8	0.6	−2.2	0.7	0.3	0.2	1.0	0.4
	Other DM equity	−0.6	0.5	−0.0	−0.0	1.9	1.7	−2.8	0.8	1.0	0.1	2.9	2.1
	EM equity	−2.3	−0.2	−2.8	−5.2	−6.9	−11.1	−3.3	−0.4	−4.7	−7.6	−9.4	−13.5
	Europe bond	15.8	−2.5	1.2	6.3	5.1	13.9	13.5	−3.4	2.9	4.8	5.5	13.2
	USA bond	−9.6	5.2	4.1	3.9	3.5	−0.3	−5.0	3.7	2.4	−3.0	−0.7	−5.0
	Other DM bond	−9.2	2.7	1.5	−1.2	−1.2	−5.9	−5.0	4.4	−0.7	3.2	−1.7	−3.3
	EM bond	3.1	−5.4	−6.8	−9.0	−7.4	−7.7	−3.5	−4.7	−4.6	−5.0	−3.1	−4.9

Following the previous remark, we report the portfolio reallocations resulting from a 10% reduction in physical risk in Table 22. For benchmark #1 (European/balanced profile), the aggregated scores (ND-GAIN, readiness, and vulnerability) indicate a significant decrease in exposure to U.S. equities and bonds. This is accompanied by a reduced allocation to emerging market equities and an increased allocation to Europe and other developed markets. The readiness score is the only exception, suggesting a slight increase in U.S. exposure (+0.7%). When portfolios are constructed using the exposure metric, the reallocation is concentrated entirely in the European bucket. Conversely, portfolios based on capacity and sensitivity remain close to the benchmark, requiring only minor adjustments to individual weights. Notably, the sensitivity-based portfolio shifts some European bond exposure toward the U.S. and moves some European equity holdings toward other developed markets. This is consistent with the relatively high sensitivity observed in some European countries. For benchmark #2 (European/aggressive profile), allocations generally tilt further toward Europe. At the same time, capacity- and sensitivity-based portfolios display patterns similar to those observed for the balanced profile. These portfolios are more diversified and closer to the benchmark composition. For benchmarks #3 and #4 (American/balanced and American/aggressive profiles), strategies based on the aggregated ND-GAIN score lead to implausible reallocations. Both profiles show a significant shift away from U.S. assets and toward European exposures. Portfolios driven by readiness, vulnerability, and exposure metrics also imply an excessive reduction in U.S. weights. These portfolios often lead to the near-complete elimination of U.S. bond holdings while reducing U.S. equity exposure more moderately. In contrast, portfolios based on capacity and sensitivity deliver more balanced and economically plausible outcomes for U.S. investors. These portfolios result in reallocations that are more gradual and preserve substantial U.S. exposure. Overall, reallocations appear to be more coherent for benchmark #5 (Global/balanced profile). European equity allocations increase across all metrics except sensitivity, and European bond allocations rise even more sharply. U.S. equity weights increase modestly under most metrics, except for the exposure-based allocation. U.S. bond holdings only decline under the ND-GAIN and exposure frameworks. Allocations to other developed markets decrease significantly in the bond bucket when ND-GAIN or exposure scores are applied. Exposure to emerging markets is consistently reduced, with bond allocations eliminated entirely in all cases except when using the exposure score. No material differences emerge between the balanced and aggressive global profiles.

Remark 3. *One important implication of our results is that home bias significantly impacts the feasibility of reducing physical risk. When investors are located in regions with relatively low physical risk, achieving high targeted reduction rates becomes more difficult. In these cases, the benchmark portfolio approaches the minimum attainable level of physical risk, leaving little room for improvement through reallocation alone. Consequently, imposing stringent physical risk reduction targets forces optimization to focus excessively on a small subset of countries, often resulting in highly concentrated portfolios. For example, this mechanism is particularly pronounced for Switzerland-centric benchmarks. Thus, the effectiveness of physical risk constraints hinges on the risk metric employed, the geographical composition of the benchmark portfolio, and the investor's home region.*

3.2.3 Financial impact of implementing physical risk mitigation

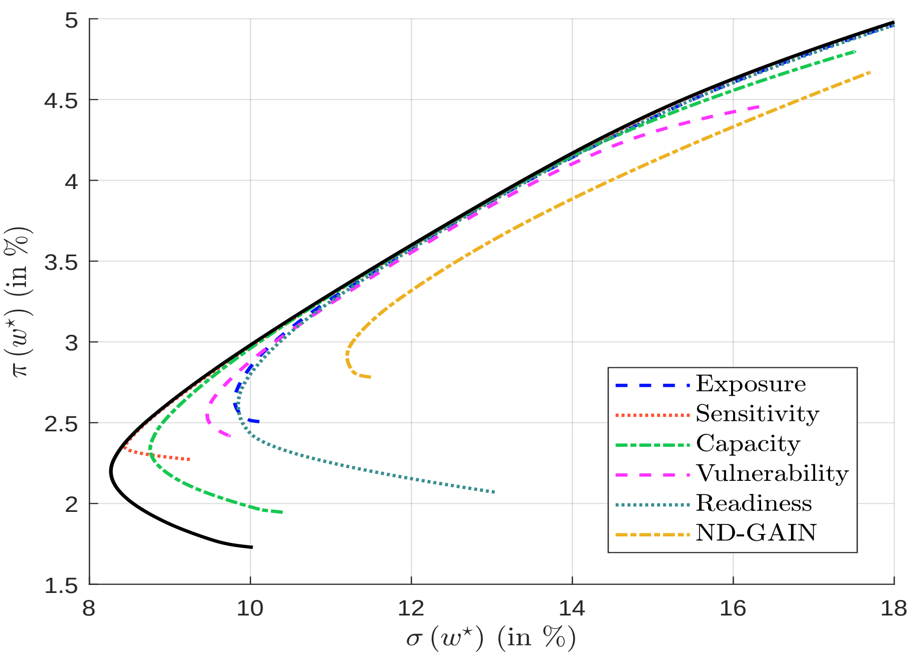
We now consider the portfolio optimization framework (2) by assuming that the vector of risk premia is specified in a manner consistent with the Black-Litterman approach:

$$\pi = \mathrm{SR}\left(b \mid r\right) \frac{\Sigma b}{\sqrt{b^\top \Sigma b}} \tag{4}$$

where $\text{SR}\left(b \mid r\right)$ is the Sharpe ratio of the benchmark portfolio relative to the risk-free rate and is set to 0.30, and Σ is the covariance matrix estimated using six years of historical data.

Impact of physical risk constraints on the mean-variance efficient frontier Figure 13 shows the Markowitz efficient frontier[35] without any physical risk constraints (black line). We compare this baseline efficient frontier with six alternative efficient frontiers computed under physical risk reduction constraints, corresponding to the six physical risk metrics considered in the analysis (exposure, sensitivity, adaptive capacity, vulnerability, readiness, ND-GAIN). For Portfolio #1 (European/balanced), imposing constraints on the sensitivity or capacity score has little effect on the risk-return trade-off compared to the Markowitz frontier. Moreover, we only observe modest shifts in the exposure, vulnerability, and readiness scores. Similar results[36] are seen for Portfolio #2 (European/aggressive). By contrast, incorporating the ND-GAIN index produces a significant shift. For any given expected return, portfolios that include the ND-GAIN index are consistently riskier. This effect is amplified for the aggressive profile, whose efficient frontier is also noticeably contracted and less smooth.

Figure 13: Mean-variance efficient frontier (Portfolio #1, $\mathcal{R} = 10\%$)



For portfolios #3 and #4 (American/balanced and American/aggressive), incorporating physical score constraints results in efficient frontiers that are usually significantly different to the Markowitz benchmark[37]. This effect is particularly pronounced for the readiness score. Furthermore, portfolios constructed using the aggregate ND-GAIN index produce completely shifted frontiers relative to the baseline. These frontiers are notably contracted and irregularly shaped, particularly for the balanced profile. These findings suggest that

[35] We solve the optimization problem (2) by assuming that the risk premia are given by Equation (4).

[36] See Figure 20 on page 88.

[37] See Figures 21 and 22 on page 88.

the physical risk constraints may be excessively stringent, resulting in feasibility issues in the optimisation procedure. By contrast, for Portfolios #5 and #6, imposing physical risk constraints has a limited impact on the risk-return trade-off. Indeed, there is no significant alteration to the shape of the efficient frontier for the Global/balanced and Global/aggressive profiles[38]. These results are consistent with the previous analysis based on the portfolio optimisation framework (3). In particular, constraints based on physical risk scores significantly alter the portfolio for American investors and are sometimes not feasible. For European investors, however, the impact is comparatively modest, especially when the constraints concern sensitivity and capacity, and the resulting strategies remain feasible. Finally, for the global investor profile, the constrained strategies appear to be the most practical, as the efficient frontiers are reasonably close to the baseline.

Cost estimation of physical risk We now consider the following σ-problem:

$$w^\star = \arg\max w^\top \pi \quad \text{s.t.} \quad \begin{cases} \sigma(w) \leq \sigma(b) \\ \boldsymbol{\mathcal{PR}}(w) \leq (1-\mathcal{R})\,\boldsymbol{\mathcal{PR}}(b) \\ w \in \Omega \end{cases} \tag{5}$$

We define the cost of the constraint as the difference between the risk premium of the constrained optimal portfolio $w^\star$ and that of the benchmark portfolio b:

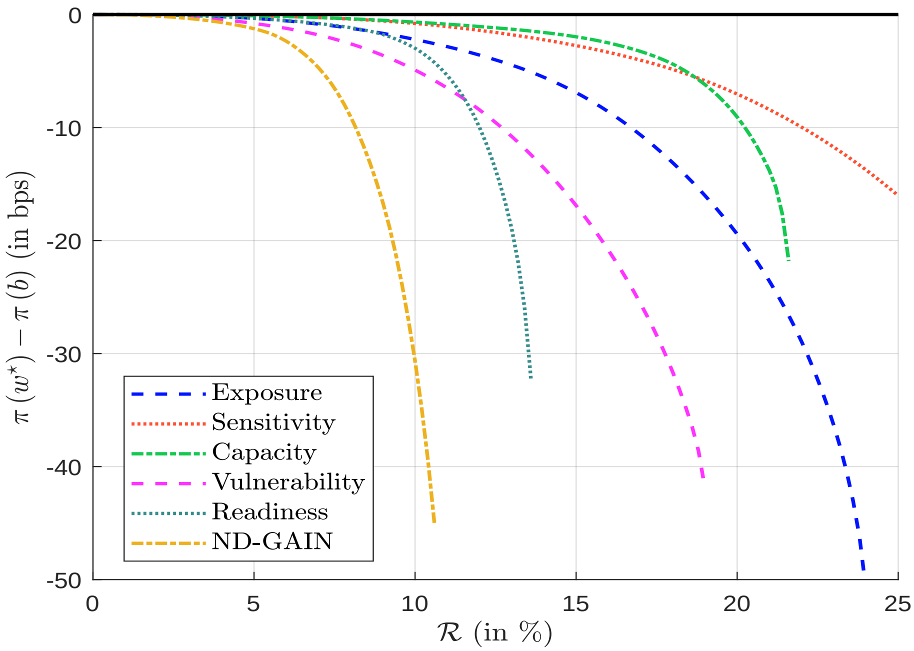
$$\mathcal{C}_{ost}(\mathcal{R}) = \pi(w^\star) - \pi(b) = (w^\star - b)^\top \pi$$

This cost represents the loss in expected return resulting from the implementation of the physical risk reduction constraint by investing in a portfolio that has the same volatility than the benchmark portfolio.

Figure 14 reports the results for Portfolio #1 (European/balanced). The financial cost remains below 10 bps in absolute value for all strategies until $\mathcal{R} = 10\%$, with the sole exception of the strategy based on the ND-GAIN index. For that strategy, once the threshold $\mathcal{R} \approx 8\%$ is exceeded, the financial cost becomes highly sensitive to $\mathcal{R}$. Small increases in $\mathcal{R}$ produce large changes in cost, resulting in a near-vertical decline toward more negative costs. For the remaining strategies, the analogous regime of extreme sensitivity occurs at higher $\mathcal{R}$. For the readiness-based strategy, the critical threshold is approximately $\mathcal{R} \approx 12\%$. The strategy based on sensitivity exhibits a substantially more linear behavior. The loss in expected return remains below 10 bps up to $\mathcal{R} \approx 22\%$. Similar patterns are observed for Portfolio #2 (European/aggressive). For the American/balanced and American/aggressive profiles[39], the financial cost associated with strategies based on the ND-GAIN and readiness scores declines more sharply than in the European case. For the other strategies the cost remains below 10 bps up to $\mathcal{R} = 10\%$. Beyond this point, expected return losses increase more rapidly than for European portfolios, particularly for sensitivity and capacity strategies. The global profiles display more balanced behavior[40]. The rapid decline in financial cost for ND-GAIN and readiness occurs at higher values of $\mathcal{R}$ than in the European or American cases. Strategies based on vulnerability and exposure maintain costs below 10 bps up to $\mathcal{R} \approx 15\%$, whereas for sensitivity and capacity, the threshold at which substantial losses occur exceeds $\mathcal{R} \approx 20\%$. In summary, the ND-GAIN and readiness measures are associated with the largest expected return losses at a comparatively low level of $\mathcal{R}$, across

[38] See Figures 23 and 24 on page 89.
[39] See Figures 26 and 27 on page 91.
[40] See Figures 28 and 29 on page 92.

Figure 14: Financial cost $\mathcal{C}_{ost}(\mathcal{R})$ of physical risk (Portfolio #1)



investor profiles. This suggests that these approaches are not suitable for practical implementation. In contrast, strategies aimed at reducing capacity and sensitivity are compatible with acceptable expected-return losses at moderate value of $\mathcal{R}$.

Shadow pricing of physical risk Building on the previous analysis, we estimate the shadow price of implementing physical risk constraints in portfolio management. Shadow pricing is a useful tool in cost-benefit analysis for estimating the willingness to pay/accept when facing negative externalities (Roncalli, 2026, pages 979–985). For example, the social cost of carbon is a shadow price used to measure transition risk at the macro-economic level (Nordhaus, 2014). In what follows, the estimated shadow price is strongly related to the previous analysis in the sense that the latter provides an estimation of the average total cost, whereas the analysis below provides an estimation of the marginal cost of physical risk. To this end, we use duality theory and consider the following utility optimization problem:

$$\begin{aligned} w^\star &= \arg\max \boldsymbol{\mathcal{U}}(w) = w^\top \pi - \frac{1}{2}\phi_b w^\top \Sigma w \\ &\text{s.t.} \quad \left\{ \begin{array}{l} \boldsymbol{\mathcal{PR}}(w) \leq (1-\mathcal{R})\, \boldsymbol{\mathcal{PR}}(b) \\ w \in \Omega \end{array} \right. \end{aligned} \tag{6}$$

where $\phi_b = \gamma_b^{-1}$ is the risk aversion parameter of the quadratic utility function, and γ_b is the risk tolerance associated with the benchmark portfolio:

$$\gamma_b = \frac{\sigma(b)}{\mathrm{SR}(b \mid r)} = \frac{\sigma^2(b)}{\pi(b)}$$

Let $\lambda^\star \geq 0$ be the Lagrange multiplier associated with the physical risk constraint $\boldsymbol{\mathcal{PR}}(w) \leq (1-\mathcal{R})\, \boldsymbol{\mathcal{PR}}(b)$. At optimality, the Lagrange function satisfies:

$$\mathcal{L}(w^\star; \lambda^\star) = \boldsymbol{\mathcal{U}}(w^\star) - \lambda^\star \left(\boldsymbol{\mathcal{PR}}(w^\star) - (1-\mathcal{R})\, \boldsymbol{\mathcal{PR}}(b)\right)$$

Suppose that the physical risk threshold is relaxed by a small amount ε. Then, the Lagrange function becomes:

$$\mathcal{L}_{\varepsilon}\left(w^{\star};\lambda^{\star}\right)=\mathcal{L}\left(w^{\star};\lambda^{\star}\right)+\lambda^{\star}\varepsilon=\left(w^{\star\top}\pi+\lambda^{\star}\varepsilon\right)-\frac{1}{2}\phi_b w^{\star\top}\Sigma w^{\star}$$

The expected return of the portfolio is improved by the amount $\lambda^{\star}\varepsilon$, meaning that $\lambda^{\star}$ is the shadow price for one unit of physical risk. In what follows, we report the normalized price $\mathcal{P}_{rice}\left(\mathcal{R}\right)=100\times\lambda^{\star}$ expressed in basis points of return per 1% of physical risk score[41].

Table 23: Shadow price of physical risk (in basis points per 1% of risk score)

Portfolio	Reduction rate $\mathcal{R}$	Exposure	Sensitivity	Capacity	Vulnerability	Readiness	ND-GAIN
	1%	0.05	0.01	0.02	0.13	0.02	0.11
#1	5%	0.41	0.23	0.21	1.18	0.26	1.01
	10%	1.27	0.96	0.62	4.31	2.12	24.35
	15%	3.36	2.14	1.50	10.73	23.67	∞
	20%	6.70	4.96	8.88	44.16	∞	∞
	1%	0.04	0.02	0.02	0.13	0.03	0.11
#2	5%	0.47	0.26	0.23	1.10	0.36	1.67
	10%	1.59	1.04	0.66	3.87	5.17	36.19
	15%	3.58	2.03	3.70	12.20	48.28	∞
	20%	6.89	4.37	18.97	49.97	∞	∞
	1%	0.08	0.04	0.05	0.18	0.06	0.19
#3	5%	0.62	0.41	0.45	1.65	3.64	8.41
	10%	1.91	1.40	5.01	6.98	26.86	71.42
	15%	3.36	3.74	16.53	24.84	108.21	∞
	20%	6.97	8.29	79.05	83.15	∞	∞
	1%	0.07	0.03	0.04	0.15	0.06	0.17
#4	5%	0.69	0.52	0.38	1.28	1.39	4.65
	10%	1.73	1.92	1.88	6.56	26.68	61.80
	15%	5.18	4.62	17.55	35.84	66.63	∞
	20%	11.20	15.87	67.06	72.56	∞	∞
	1%	0.05	0.03	0.02	0.09	0.03	0.08
#5	5%	0.48	0.32	0.20	0.93	0.30	0.94
	10%	1.33	0.96	0.48	2.24	1.26	5.07
	15%	3.14	1.73	1.13	5.08	5.39	40.74
	20%	5.11	3.36	2.09	12.67	38.21	∞
	1%	0.05	0.03	0.02	0.10	0.03	0.08
#6	5%	0.45	0.30	0.19	0.80	0.33	1.03
	10%	1.76	0.93	0.62	2.50	1.32	4.76
	15%	3.52	2.43	1.35	5.81	6.03	47.80
	20%	6.66	4.33	2.15	16.13	43.66	∞

[41] In practice, we solve the QP problem $w^{\star}=\arg\min\frac{1}{2}w^{\top}\Sigma w-\gamma_b w^{\top}\pi$ subject to the constraints $\boldsymbol{\mathcal{PR}}\left(w\right)\leq\left(1-\mathcal{R}\right)\boldsymbol{\mathcal{PR}}\left(b\right)$ and $w\in\Omega$. Then, we have $\lambda^{\star}=\gamma_b^{-1}\lambda^{*}$, where λ^{*} is the Lagrange multiplier associated with the physical risk constraint $\boldsymbol{\mathcal{PR}}\left(w\right)\leq\left(1-\mathcal{R}\right)\boldsymbol{\mathcal{PR}}\left(b\right)$.

Table 23 reports the shadow prices for all strategies. These values measure the marginal loss in expected return (in basis points) required to reduce the physical risk score by 1% (or to increase it in the case of readiness and the ND-GAIN index). Across portfolios and investor profiles, the shadow price increases with the stringency parameter $\mathcal{R}$. Initial reductions in physical scores can be achieved at a relatively modest cost, but the marginal cost rises rapidly as the stringency parameter $\mathcal{R}$ becomes more restrictive. The aggregated ND-GAIN index has the highest shadow prices, followed by readiness and vulnerability. In particular, there is a significant jump in marginal costs when $\mathcal{R}$ increases from 5% to 10%, indicating a strong trade-off between portfolio performance and physical score improvement. This effect is especially pronounced for the U.S.-focused profiles (Portfolios #3 and #4). For example, the shadow price of raising the readiness score increases from 3.64 bps to 26.86 bps for Portfolio #3 and from 1.39 bps to 26.68 bps for Portfolio #4 as $\mathcal{R}$ increases from 5% to 10%. By contrast, the marginal cost of reducing exposure, sensitivity, and capacity scores remains very low — below two basis points — for all selected portfolios up to $\mathcal{R} = 10\%$, with the exception of Portfolio #3 for a 10% reduction in capacity. Overall, moderate reductions in physical scores can be achieved at a relatively low cost. However, beyond certain thresholds, the shadow price increases sharply. This trade-off is particularly acute for the ND-GAIN index and portfolios with concentrated U.S. exposure.

4 Conclusion

While investors and portfolio managers have become highly familiar with transition risk, physical risk remains relatively obscure in the asset management industry. Over the past decade, there has been remarkable enthusiasm for climate finance, particularly following the publication of seminal research by Andersson *et al.* (2016) on carbon risk and portfolio management. Concepts such as carbon intensity, portfolio decarbonization, green bonds, net-zero investing, greenness scores, and climate-aligned impact investing are now widely used and understood by institutional investors. However, these concepts and metrics primarily relate to transition risk rather than physical risk. For a long time, the financial sector largely viewed physical risk as an insurance risk, associated with rare and extreme natural catastrophes. However, this perspective has become inadequate in the context of climate change. First, the growing frequency and severity of climate-related hazards have widened the insurance protection gap, with potentially significant consequences for firms and households and their capacity to absorb shocks. As a result, physical risk has emerged as a structural component of credit risk, with important implications for the financial system, including indirect spillovers to banks and institutional investors. Second, physical risk cannot be reduced to acute events such as hurricanes or floods. It also encompasses chronic risks, including rising temperatures and sea level rise. These developments generate persistent pressure on business models and operations, affecting operational performance and strategic positioning. In this broader sense, physical risk has become a significant driver of business risk, with far-reaching implications for asset valuation and portfolio construction.

Physical risk is not transition risk. This distinction is clear from their definitions. Transition risk refers to the economic and financial costs associated with shifting toward a low-carbon economy, whereas physical risk relates to direct losses caused by climate change related hazards. Beyond terminology, the two types of risk differ in asset management for several fundamental reasons. The first difference lies in their measurement. Transition risk is primarily assessed using direct, observable data such as carbon intensity, green revenue share, and fossil fuel exposure[42]. By contrast, physical risk is generally evaluated

[42]These direct metrics may be complemented by model-based or forward-looking indicators, such as tem-

Table 24: Carbon intensity and S&P physical risk scores (2030 medium scenario) of MSCI World Index and MSCI EM Index (November 2025)

	Carbon intensity				2030 Medium scenario			
	$\mathcal{CI}_{1-3}^{\text{up}}$		$\mathcal{CI}_{1-3}$		$\mathcal{PE}$		$\mathcal{SE}$	
	DM	EM	DM	EM	DM	EM	DM	EM
Communication Services	75	86	107	111	57.9	57.3	20.1	18.9
Consumer Discretionary	142	187	443	943	56.5	62.0	32.9	33.1
Consumer Staples	233	384	595	563	57.3	60.7	31.6	42.9
Energy	579	842	3 982	6 751	57.5	62.9	35.7	47.1
Financials	24	32	1 908	2 242	57.1	62.5	14.4	19.9
Health Care	82	161	100	173	57.4	59.0	22.6	41.7
Industrials	191	310	4 305	5 901	56.7	59.6	30.3	39.0
Information Technology	106	249	317	383	58.2	61.4	17.6	43.2
Materials	776	1 559	2 023	2 989	59.5	64.4	43.4	52.9
Real Estate	117	191	347	627	54.9	64.5	33.3	42.3
Utilities	1 408	3 811	2 358	4 455	57.4	62.6	44.2	48.8
Total	180	379	1 240	1 755	57.5	61.4	23.9	35.1
Median	100	187	403	879	56.0	60.0	29.0	38.0
Standard deviation	479	1 584	3 658	5 988	4.4	6.8	12.5	14.4
Coefficient of variation (in %)	478	848	908	681	7.9	11.3	43.2	37.8

Source: S&P Global, MSCI and Authors' calculations.

through composite risk scores[43]. This difference is crucial. Direct data measurement relies on relatively transparent variables, whereas scoring systems depend heavily on modeling assumptions, scenario choices[44], hazard projections, geographic mapping, and aggregation methods. As a result, physical risk assessments tend to be more sensitive to methodological choices and embedded assumptions than transition risk metrics. The second distinction concerns the conceptual framework. In financial literature, physical risk is typically structured around the three-dimensional hazard/exposure/vulnerability framework. Hazard depends on the climate scenario and the associated evolution of extreme and chronic events. Exposure reflects the geographic and operational footprint of firms and therefore depends on scenario-dependent climate projections. Vulnerability captures the sensitivity and adaptive capacity of firms, sectors, or regions, and relies on assumptions about technological adaptation, infrastructure resilience, and institutional preparedness. In other words, physical risk is inherently scenario-based and forward-looking. Each dimension is subject to modeling uncertainty, particularly the vulnerability dimension. The third difference is the generally low correlation between transition and physical risks. Transition risk is concentrated in a few number of carbon-intensive sectors, such as energy, utilities, and materials (Table 24). By contrast, physical risk potentially affects all sectors of the economy since every firm operates within a physical environment that is exposed to climate hazards. In this sense, exposure to physical risk has a systemic dimension, because the entire economic system is exposed to

perature alignment scores. However, observable emissions and activity-based measures remain the core inputs in most transition risk analyses.

[43] It is relatively straightforward to measure the realized losses associated with a specific past hazard, such as a flood or hurricane. Therefore, historical databases of catastrophe losses are well developed. However, these data are of limited relevance for assessing future physical risk (*e.g.*, in 2030 or 2050), because climate change makes hazard frequencies and intensities non-stationary. Moreover, physical risk is multidimensional, encompassing various hazards (*e.g.*, heat stress, floods, droughts, storms, and sea level rise), which complicates aggregation. For these reasons, forward-looking scoring methodologies are commonly used instead of purely historical loss data.

[44] Tables 24 and 25 report the S&P physical scores for 2030 medium, 2050 medium and 2050 high scenarios.

climate-related hazards to varying degrees. Our empirical results confirm this distinction, as we find zero or low correlation between standard transition risk metrics and measures of physical risk exposure. The relationship is somewhat more nuanced for vulnerability, where certain transition-related indicators may be positively correlated with physical risk sensitivity. However, when these dimensions are incorporated into portfolio optimization, climate risk-managed portfolios exhibit limited overlap between transition and physical risk constraints. This confirms that they are largely distinct sources of financial risk.

Table 25: S&P physical risk scores (2050 medium and high scenario) of MSCI World Index and MSCI EM Index (November 2025)

	2050 Medium scenario				2050 High scenario			
	$\mathcal{PE}$		$\mathcal{SE}$		$\mathcal{PE}$		$\mathcal{SE}$	
	DM	EM	DM	EM	DM	EM	DM	EM
Communication Services	63.3	64.3	23.5	21.9	67.8	68.5	26.1	24.1
Consumer Discretionary	62.3	67.4	37.3	37.4	66.9	71.7	41.4	41.1
Consumer Staples	63.1	66.3	35.9	47.9	68.0	70.9	39.8	52.2
Energy	62.7	68.1	39.8	51.7	67.4	72.3	43.5	55.5
Financials	63.1	67.8	16.4	23.3	67.8	72.1	18.3	26.3
Health Care	63.3	64.9	26.0	47.0	68.0	69.4	28.9	51.1
Industrials	62.7	65.3	34.6	43.9	67.5	70.1	38.4	48.4
Information Technology	64.1	66.5	20.4	47.7	68.9	71.5	23.3	52.5
Materials	65.2	69.8	48.2	57.9	69.8	74.0	52.2	61.8
Real Estate	61.1	69.9	38.1	47.0	65.8	73.8	42.3	51.0
Utilities	62.8	68.7	49.0	54.0	67.5	73.4	53.3	58.0
Total	63.3	66.9	27.3	39.3	68.0	71.5	30.4	43.1
Median	62.0	66.0	34.0	44.0	67.0	71.0	37.0	48.4
Standard deviation	4.0	5.8	13.9	15.2	3.7	5.1	14.9	15.8
Coefficient of variation (in %)	6.5	8.8	40.8	34.6	5.5	7.3	40.2	32.7

Source: S&P Global, MSCI and Authors' calculations.

One important implication of these differences is that portfolio optimization under physical risk mitigation cannot be directly compared to optimization under transition risk constraints. The economic trade-offs, feasibility, and portfolio reallocation mechanisms differ substantially. First, consider transition risk. From an optimization perspective, portfolio decarbonization is relatively straightforward. A decade ago, it was particularly easy when investors focused exclusively on Scope 1 and 2 emissions. However, the inclusion of Scope 3 emissions has made the process more demanding, as carbon footprints are more broadly distributed across sectors and value chains. Nevertheless, reducing portfolio carbon intensity by 30% to 50% typically generates an acceptable level of tracking error for most institutional investors. Such reductions can often be achieved through moderate sector tilts and stock selection within high-emitting industries without fundamentally altering the portfolio's risk-return profile. The case of net-zero investing is more complex, since transition risk is generally proxied by carbon intensity and green intensity. However, the current positive correlation between carbon intensity and green intensity complicates portfolio construction. Firms with high green revenues are often still carbon-intensive, reflecting the transitional nature of many sectors. This structural feature limits the scope for simultaneously minimizing carbon exposure while maximizing green exposure without incurring higher tracking error. In addition, portfolio self-decarbonization — that is, the endogenous reduction in carbon intensity due to corporate transition efforts — has remained limited, at below 3% per year over the past two years. Consequently, achieving net-zero alignment requires active reallocation and rebalancing rather than relying on organic improvements. Despite these constraints, constructing net-zero portfolios remains feasible through approaches such as integrated optimization or core-satellite allocation strategies (Barahhou *et al.*, 2022; Ben Slimane *et al.*, 2023). Empirically, the tracking error of such portfolios remains within acceptable bounds, provided that the initial decarbonization pathway is not excessively aggressive. For example, following a Climate Transition Benchmark (CTB) trajectory — implying a carbon intensity reduction of approximately 30% to 40% — appears operationally realistic[45]. Even at these levels, the reduction is substantial and economically significant. However, the situation differs markedly when it comes to mitigating physical risk. Our simulations show that reducing physical risk exposure by more than 10% results in a disproportionate increase in tracking error. Similarly, reducing physical risk vulnerability by more than 20% appears unrealistic within a diversified, benchmark-constrained framework. Unlike transition risk, physical risk is not concentrated in a few sectors that can easily be underweighted. Because exposure to climate hazards is widespread geographically and operationally, meaningful reductions require aggressive reallocations that conflict with standard diversification. In short, transition risk mitigation can be implemented through relatively targeted sector and factor adjustments. However, physical risk mitigation is structurally more constrained. The systemic nature of physical risk limits the degrees of freedom available to portfolio managers, making large reductions significantly more costly in terms of tracking error. This reinforces the conclusion that transition and physical risks present fundamentally different challenges in portfolio construction.

Tables 24 and 25 highlight several key findings of our analysis. First, we notice that the dispersion of the physical risk exposure score is relatively low. The coefficient of variation is generally below 10%, whereas it exceeds 30% for the physical risk sensitivity score and surpasses 400% for carbon intensity. This difference in cross-sectional dispersion is economically significant. Low dispersion implies limited differentiation across firms, reducing the degrees of freedom available in portfolio optimization. Additionally, we found that the discrepancy between developed market (DM) and emerging market (EM) stocks with respect to physical risk exposure is modest. This contrasts with many transition risk indicators, where regional and sectoral differences are more pronounced. The limited dispersion across firms and regions reinforces the idea that physical risk exposure has a systemic dimension. Consequently, attempts to substantially reduce exposure tend to necessitate extensive and costly deviations from the benchmark. In contrast, the dispersion of physical risk sensitivity, or vulnerability, is significantly greater. This greater heterogeneity creates more room for optimization. Empirically, vulnerability is easier to reduce than exposure. However, optimization is far more constrained in this case than in the case of transition risk. For instance, the coefficient of variation of carbon intensity is at least ten times higher than that of physical risk sensitivity. Overall, these results suggest a clear hierarchy of mitigation feasibility. Reducing carbon intensity (transition risk) is comparatively straightforward due to high cross-sectional dispersion. Reducing physical risk vulnerability is more difficult, though feasible, for low reduction rates. Reducing physical risk exposure, however, is particularly complex or impossible due to its low dispersion and systemic nature. The second key finding is that the choice of climate scenario and time horizon has a stronger impact on exposure than on vulnerability. Tables 24 and 25 show that median exposure scores increase with scenario severity and time horizon length while standard deviations decrease. In contrast, sensitivity (or vulnerability) increases as scenarios become more severe and distant, as indicated by rising median scores and standard deviations. These patterns imply opposite effects on cross-sectional dispersion. Physical risk exposure becomes increas-

[45] By contrast, the Paris-Aligned Benchmark (PAB) trajectory may be excessively stringent, particularly in light of the recent global greenhouse gas emissions trend.

ingly homogeneous across firms under more severe and longer-term scenarios, as reflected by the declining standard deviation. Conversely, physical risk vulnerability becomes more dispersed, indicating greater differentiation across firms. In other words, the progression of climate scenarios reduces heterogeneity in exposure but amplifies heterogeneity in vulnerability. The third key finding is that sectors are impacted differently when mitigating transition versus physical risk. It is commonly accepted that "*portfolio decarbonization is a strategy that is long on Financials and short on Energy, Materials and Utilities*" (Barahhou *et al.*, 2022, page 37). This characterization is generally accurate when carbon footprints are measured using Scope 1, Scope 2, and Scope 3 upstream emissions. However, recent revisions to the methodology for calculating Scope 3 downstream emissions suggest that the carbon footprint of the Financials sector has been underestimated in recent years. Using more recent data, we notice that the Financial sectors remains a low carbon-intensive sector when we consider scopes 1, 2 and 3 upstream emissions, but a high carbon-intensive sector when scope 3 downstream emissions are included, due to indirect financed emissions arising from loans, mortgages and other credit exposures. Table 24 illustrates how Scope 3 downstream emissions affect the carbon footprint of different sectors. The figures explain why portfolio decarbonization becomes short on the Financials sector when considering the complete Scope 3 carbon intensity. Otherwise, the results align with previous publications (Barahhou *et al.*, 2022; Ben Slimane *et al.*, 2023). For realistic values of the reduction rate $\mathcal{R}$, the impact of mitigating physical risk exposure is limited. Regarding vulnerability, curiously, we find that the strategy is long on Financials and short on Energy, Materials, and Utilities. This result holds for both the MSCI World Index and the MSCI EM Index. One possible explanation is that ESG data providers are in the early stages of estimating physical risk. Currently, physical risk is mainly assessed through direct effects, with indirect effects only partially included. Since vulnerability risk is primarily measured through direct damage to assets, sectors such as Financials have an advantage because their assets are intangible. However, we may see a future shift similar to what we have seen with carbon footprint metrics. Indeed, we can anticipate that the indirect effects of physical risk on the Financials sector are currently underestimated, because the vulnerability of other economic actors, such as firms and households, serves as a transmission channel to this sector.

In addition to analyzing the mitigation of physical risk in equity portfolio management, our study examines another challenge in asset management, which is the construction of strategic asset allocation. Specifically, we investigate how physical risk affects regional allocation using the ND-GAIN database to evaluate its various dimensions. In addition to exposure and sensitivity, the database provides indicators of adaptive capacity and readiness, as well as two composite scores. The vulnerability score combines exposure, sensitivity, and adaptive capacity, while the overall ND-GAIN score integrates vulnerability and readiness. Our analysis considers three types of investors (European, American, and global) and two risk profiles (balanced and aggressive). We find that changes in regional allocations depend on the specific dimension of physical risk considered[46] and on the benchmark allocation. Indeed, we find that home bias significantly impacts the feasibility of reducing physical risk. Where the initial physical risk is already low, improving the benchmark through reallocation alone is complex. Very stringent targets can therefore cause extreme concentrations (*e.g.*, Switzerland or Sweden in the European component using aggregated scores). Introducing additional diversification constraints that penalize concentration by country could avoid these outcomes. Overall, however, we observe a shift away from American and emerging market assets toward European assets. This result varies across risk dimensions. The shift

[46]We find that the ND-GAIN index and the readiness score are the most difficult to improve. The maximum achievable increases are 16.5% and 23.8%, respectively. By contrast, the exposure, sensitivity and capacity sub-scores are easier to improve, although their maximum reduction rates do not exceed 40%.

holds when using the overall ND-GAIN score[47], whereas the sensitivity and adaptive capacity dimensions are generally associated with higher exposure to American assets. These results imply that the choice of risk metric is not neutral. As in the case of equity portfolio management, mitigating physical risk has a substantial impact on portfolio construction. Again, even if we use a completely different database to measure physical risk, targeting high reduction rates is infeasible. By *high reduction rates*, we mean reductions exceeding 10%. Therefore, this second asset management exercise confirms that climate-conscious institutional investors cannot pursue the same level of ambition for physical risk as they do for transition risk. Our estimates of the average cost and shadow price of physical risk indicate a substantial effect on the portfolio's risk-return profile. Since shadow prices can exceed 10 basis points for each 1% decrease in the risk score, the trade-off between financial performance and environmental objectives becomes more pronounced[48].

In summary, physical risk differs fundamentally from transition risk and poses a greater challenge from an asset management perspective. Reducing exposure to physical risk is particularly difficult due to its systemic nature. In contrast, other dimensions, such as vulnerability and adaptive capacity, seem comparatively easier to address in portfolio construction. At the same time, the measurement of physical risk remains imperfect. Existing metrics are still relatively coarse and require further refinement to support robust investment decisions. However, recent trends in greenhouse gas emissions and the slowdown in climate policy ambition suggest that asset managers must be prepared to confront increasing physical risk. Our findings suggest that there is less room for maneuver than in the case of transition risk. The next five years will therefore be critical for the asset management industry as it adapts to this evolving risk landscape.

[47] For example, applying a 10% improvement to the ND-GAIN index produces a 33% decline for the American/balanced profile when U.S. equity weight is 40%, and a 40.7% decline for the aggressive profile when U.S. equity weight is 60%. U.S. bond exposure falls to zero.

[48] For example, increasing the ND-GAIN index rate $\mathcal{R}$ from 5% to 10% raises the shadow price from 1.01 bps to 24.35 bps for a European/balanced investor, and from 8.41 bps to 71.42 bps for an American/balanced investor. Likewise, increasing the readiness score rate $\mathcal{R}$ from 10% to 15% increases the shadow price for the European/balanced profile from 2.12 bps to 23.67 bps, and for the American/balanced profile from 26.86 bps to 108.21 bps.

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A Data

For the company level analysis, the transition and physical risk metrics (carbon intensity, exposure and sensitivity scores) are sourced from the S&P Global database (S&P Global Trucost and S&P Global Sustainable1), while green intensity measures are obtained from Amundi database. Carbon-intensity values are for the year 2023, to maximize the number of firms with available data, and refer to the tonnes of CO_2e equivalent emitted per million of USD of revenues ($tCOtwoEq$/\$ mn). We also use the composition of the MSCI World Index as of 17 November 2025, and the composition of the MSCI EM Index as of 8 December 2025. For both indices, we use nearly three years of daily return data (2 January 2023 – 18 November 2025). Missing values in climate-risk metrics are filled using the sector-weighted average of the respective measure. In the case of the SAA exercise, we use the Datastream indices (DS Market Index for equities and TOTAL ALL LIVES DS GOVT. INDEX for bonds). For each index, we consider the market value and the total return index to compute the market capitalization and the daily returns.

B Additional results

B.1 MSCI World Index

Table 26: Spearman correlation between physical risk and transition risk scores (MSCI World Index, 2030 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$	$\mathcal{GI}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	1.43	2.84	3.28	5.17	5.99	−7.01
	p-value	60.24	30.29	23.35	6.04	2.95	1.08
High	$\rho(\mathcal{PE}, \mathcal{TR})$	0.06	3.29	2.55	4.19	5.28	−6.86
	p-value	98.35	23.24	35.42	12.79	5.52	1.26
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	69.24	61.73	56.05	7.48	25.55	35.73
	p-value	0.00	0.00	0.00	0.65	0.00	0.00
High	$\rho(\mathcal{SE}, \mathcal{TR})$	68.74	61.94	55.80	7.17	25.24	35.94
	p-value	0.00	0.00	0.00	0.91	0.00	0.00

Table 27: Pearson correlation between physical risk and transition risk scores (MSCI World Index, 2090 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$	$\mathcal{GI}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	−2.71	8.51	−2.36	5.69	5.48	−7.35
	p-value	32.52	0.20	39.12	3.87	4.65	0.75
High	$\rho(\mathcal{PE}, \mathcal{TR})$	−4.01	6.49	−2.18	4.07	3.68	−6.63
	p-value	14.46	1.82	42.82	13.88	18.07	1.59
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	26.30	24.99	34.14	−0.36	4.38	26.68
	p-value	0.00	0.00	0.00	89.58	11.15	0.00
High	$\rho(\mathcal{SE}, \mathcal{TR})$	25.13	23.38	35.02	−0.72	3.88	27.42
	p-value	0.00	0.00	0.00	79.46	15.86	0.00

Table 28: Spearman correlation between physical risk and transition risk scores (MSCI World Index, 2090 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$	$\mathcal{GI}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	−0.08	3.51	2.76	5.37	6.70	−5.17
	p-value	97.54	20.18	31.62	5.07	1.49	6.03
High	$\rho(\mathcal{PE}, \mathcal{TR})$	−1.74	1.28	1.74	4.77	5.98	−4.83
	p-value	52.61	64.28	52.64	8.29	2.98	7.93
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	69.16	62.29	55.77	7.23	25.30	37.06
	p-value	0.00	0.00	0.00	0.85	0.00	0.00
High	$\rho(\mathcal{SE}, \mathcal{TR})$	69.00	62.38	55.77	6.60	24.64	37.37
	p-value	0.00	0.00	0.00	1.64	0.00	0.00

Table 29: Weighted mean of climate risk measures per country (MSCI World Index, medium scenario)

Country	n_k	b_k	$\mathcal{CI}_{1-3,k}$	$\mathcal{PE}_k^{2030}$	$\mathcal{SE}_k^{2030}$	$\mathcal{PE}_k^{2090}$	$\mathcal{SE}_k^{2090}$	$\mathcal{GI}_k$
Australia	47.0	1.6	2 252	58.9	28.2	71.0	35.0	2.6
Austria	3.0	0.1	2 747	52.9	22.5	67.6	30.4	5.4
Belgium	11.0	0.3	1 195	59.7	24.3	72.5	32.4	2.4
Canada	83.0	3.3	1 947	55.8	28.0	68.7	36.4	8.8
Denmark	15.0	0.4	902	54.5	25.2	67.7	34.4	14.5
Finland	13.0	0.3	1 352	52.9	23.6	66.6	31.7	13.3
France	57.0	2.7	1 469	57.3	27.4	70.5	36.6	13.5
Germany	54.0	2.3	2 850	56.5	22.5	69.6	30.1	15.0
Hong Kong	27.0	0.5	930	55.9	24.2	68.9	32.4	11.8
Ireland	5.0	0.1	1 108	54.1	23.0	67.1	30.6	11.4
Israel	15.0	0.3	911	64.5	20.4	75.1	27.3	1.1
Italy	25.0	0.8	2 197	57.9	23.3	70.5	30.2	8.7
Japan	180.0	5.5	2 635	55.1	26.3	67.5	34.9	11.9
Netherlands	27.0	1.2	653	56.9	20.6	69.7	28.6	0.8
New Zealand	5.0	0.0	345	50.9	36.1	66.2	50.4	22.2
Norway	11.0	0.1	2 135	51.6	24.1	65.6	33.3	15.4
Portugal	5.0	0.1	1 210	59.7	35.3	71.3	44.0	21.8
Singapore	17.0	0.4	1 515	56.0	26.4	72.2	38.7	9.8
Spain	19.0	0.9	1 520	63.8	28.5	74.8	36.9	9.1
Sweden	41.0	0.9	3 124	55.8	24.5	68.9	32.8	8.6
Switzerland	43.0	2.3	1 228	57.0	24.7	69.9	33.1	3.4
United Kingdom	73.0	3.6	1 533	57.2	26.3	70.1	34.6	4.0
United States	546.0	72.4	982	57.7	23.2	69.7	30.7	17.2

Table 30: Estimates $\hat{\beta}_k$ of the regression analysis using country dummies (MSCI World Index, medium scenario)

Country	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$	$\mathcal{GI}$
Intercept (USA)	$1\,413^{***}$	56.69^{***}	68.97^{***}	27.10^{***}	35.38^{***}	9.70^{***}
Australia	180	1.65^{***}	1.76^{***}	2.94	2.64	-3.78
Austria	663	-3.69	-1.63	1.90	3.95	6.26
Belgium	-224	2.31^{*}	2.58^{***}	-2.29	-2.20	-0.09
Canada	834^{*}	-0.77	0.17	4.56^{***}	6.15^{***}	0.29
Denmark	-469	-3.42^{***}	-2.03^{**}	0.16	1.22	13.28^{**}
Finland	-413	-4.76^{***}	-3.35^{***}	1.36	3.46	7.01
France	97	0.03	1.60^{***}	1.63	3.28	9.13^{***}
Germany	345	-0.22	0.55	-1.22	-0.90	-0.45
Hong Kong	-325	-1.09	0.52	7.64^{***}	10.88^{***}	10.19^{**}
Ireland	-371	-2.89	-1.97	-3.70	-4.18	7.78
Israel	-657	6.98^{***}	5.43^{***}	-4.10	-5.05	-6.90
Italy	429	2.31^{***}	2.43^{***}	-1.90	-2.30	-1.03
Japan	544^{*}	-2.64^{***}	-2.36^{***}	2.13^{**}	3.29^{**}	1.93
Netherlands	-559	-1.13	0.15	-6.18^{**}	-6.87^{**}	-7.51^{*}
New Zealand	$-1\,040$	-7.49^{***}	-3.97^{***}	9.30^{*}	15.82^{**}	22.39^{**}
Norway	515	-6.14^{***}	-4.42^{***}	0.26	2.25	11.53^{*}
Portugal	-202	2.91	2.23	6.10	6.22	18.03^{*}
Singapore	168	-1.98^{**}	2.27^{***}	4.54	9.38^{**}	13.10^{**}
Spain	-186	6.52^{***}	5.61^{***}	3.84	4.09	3.10
Sweden	$1\,055^{*}$	-1.66^{**}	-0.55	2.43	4.01	2.93
Switzerland	-352	-0.70	0.16	0.74	1.41	-3.60
United Kingdom	319	0.37	0.92^{**}	1.90	2.51	-1.00
$\bar{R}_c^2$	-0.64%	15.84%	18.03%	1.59%	2.38%	2.08

Table 31: Estimates $\hat{\beta}_j$ and $\hat{\beta}_k$ of the regression analysis (MSCI World Index, medium scenario)

Country	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$	$\mathcal{GI}$
Intercept (Fin/USA)	2 022***	56.80***	69.03***	12.46***	16.28***	−0.63
Communication Services	−1 945***	−0.40	−0.19	8.59***	12.12***	0.48
Consumer Discretionary	−1 498***	−0.46	−0.34	18.57***	24.29***	8.00***
Consumer Staples	−1 510***	−0.51	−0.24	19.33***	25.42***	1.96
Energy	3 042***	0.28	−0.88	22.29***	27.56***	6.78**
Health Care	−1 904***	0.47	0.44	14.51***	19.18***	0.63
Industrials	1 195***	0.06	0.17	17.09***	22.59***	17.23***
Information Technology	−1 773***	−0.34	−0.06	10.60***	14.45***	12.42***
Materials	−351	2.39***	1.92***	29.59***	36.21***	15.75***
Real Estate	−1 669***	−1.81***	−1.45***	20.48***	27.24***	28.69***
Utilities	254	−0.81	−0.79	28.09***	35.14***	31.74***
Australia	68	1.35**	1.54***	2.29	2.13	−3.27
Austria	−1 044	−3.62	−1.14	−0.25	2.16	3.75
Belgium	−67	2.10	2.41**	−0.72	0.10	4.72
Canada	58	−1.15**	0.01	2.44**	3.97***	0.10
Denmark	−761	−3.72***	−2.31***	−1.13	−0.39	13.87***
Finland	−948	−5.16***	−3.61***	−0.45	1.49	6.78
France	−61	0.02	1.56***	0.61	1.91	8.54***
Germany	370	−0.38	0.39	−2.37	−2.35	−0.04
Hong Kong	−503	−0.50	1.00	5.85***	8.50***	2.80
Ireland	−1 155	−2.92	−2.05	0.24	0.81	10.83
Israel	−374	6.93***	5.32***	0.86	1.26	−5.70
Italy	−77	2.36***	2.57***	1.95	2.91	2.47
Japan	481	−2.67***	−2.43***	1.69**	2.64***	2.06
Netherlands	−615	−1.27	−0.03	−3.51**	−3.44	−3.63
New Zealand	−1 608	−7.38***	−3.83***	6.38	12.52***	16.45
Norway	−102	−6.57***	−4.60***	−2.13	−0.32	15.62***
Portugal	−1 218	3.17	2.71	1.18	0.67	13.91
Singapore	−132	−1.64	2.52***	5.07**	9.91***	10.35**
Spain	−796	6.62***	5.76***	4.18**	4.75	1.84
Sweden	386	−1.82***	−0.73	3.12**	4.80***	1.63
Switzerland	−371	−1.10	−0.19	0.37	1.12	−1.25
United Kingdom	192	0.28	0.85**	1.39	2.00	0.39
$\bar{R}^2_c$	11.85%	18.58%	20.97%	48.81%	52.07%	21.18%

Table 32: Overlap (in %) between transition and physical risk-managed tracking portfolios (MSCI World Index, 2090 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 5\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 15\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 25\%$
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 0\%$	100.0	57.8	24.9	8.3	0.8	0.5
	$\mathcal{R} = 20\%$	93.3	59.7	25.5	8.5	0.9	0.6
	$\mathcal{R} = 40\%$	90.2	59.7	25.7	8.6	0.9	0.6
	$\mathcal{R} = 60\%$	85.3	57.6	25.4	8.4	0.9	0.5
	$\mathcal{R} = 80\%$	72.0	54.4	26.0	8.6	1.0	0.5
		$\mathcal{SE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 40\%$	$\mathcal{R} = 60\%$	$\mathcal{R} = 80\%$
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 0\%$	100.0	87.7	82.5	63.8	40.2	13.3
	$\mathcal{R} = 20\%$	93.3	90.2	81.6	63.3	39.9	13.3
	$\mathcal{R} = 40\%$	90.2	89.2	80.7	62.9	40.1	13.6
	$\mathcal{R} = 60\%$	85.3	84.6	79.4	62.8	40.7	14.2
	$\mathcal{R} = 80\%$	72.0	74.3	71.3	59.1	39.7	14.9

Table 33: Correlation (in %) between transition and physical risk-managed tracking portfolios (MSCI World Index, 2030 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 5\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 15\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 25\%$
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 0\%$	100.0	99.9	99.4	98.0	93.7	81.2
	$\mathcal{R} = 20\%$	100.0	99.9	99.5	98.0	93.7	81.2
	$\mathcal{R} = 40\%$	100.0	99.9	99.5	98.0	93.7	81.3
	$\mathcal{R} = 60\%$	100.0	99.9	99.4	98.0	93.7	81.2
	$\mathcal{R} = 80\%$	99.9	99.9	99.4	98.0	93.7	81.2
		$\mathcal{SE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 40\%$	$\mathcal{R} = 60\%$	$\mathcal{R} = 80\%$
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 0\%$	100.0	100.0	100.0	99.9	99.5	97.0
	$\mathcal{R} = 20\%$	100.0	100.0	100.0	99.9	99.5	97.0
	$\mathcal{R} = 40\%$	100.0	100.0	100.0	99.9	99.5	97.1
	$\mathcal{R} = 60\%$	100.0	100.0	100.0	99.9	99.5	97.0
	$\mathcal{R} = 80\%$	99.9	99.9	99.9	99.8	99.5	97.0

Table 34: Correlation (in %) between transition and physical risk-managed tracking portfolios (MSCI World Index, 2090 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 5\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 15\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 25\%$
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 0\%$	100.0	99.7	98.1	91.0	67.2	36.9
	$\mathcal{R} = 20\%$	100.0	99.7	98.2	91.1	67.2	36.9
	$\mathcal{R} = 40\%$	100.0	99.8	98.2	91.1	67.2	36.9
	$\mathcal{R} = 60\%$	100.0	99.7	98.1	91.0	67.1	36.8
	$\mathcal{R} = 80\%$	99.9	99.7	98.1	91.0	67.1	36.8
		$\mathcal{SE}$					
		$\mathcal{R} = 0\%$	$\mathcal{R} = 10\%$	$\mathcal{R} = 20\%$	$\mathcal{R} = 40\%$	$\mathcal{R} = 60\%$	$\mathcal{R} = 80\%$
$\mathcal{CI}_{1-3}$	$\mathcal{R} = 0\%$	100.0	100.0	100.0	99.9	99.4	96.9
	$\mathcal{R} = 20\%$	100.0	100.0	100.0	99.9	99.4	96.9
	$\mathcal{R} = 40\%$	100.0	100.0	100.0	99.9	99.5	96.9
	$\mathcal{R} = 60\%$	100.0	100.0	100.0	99.9	99.5	96.9
	$\mathcal{R} = 80\%$	99.9	99.9	99.9	99.8	99.4	96.9

Table 35: Sector allocation (in %) with constraints on $\mathcal{PE}$ (MSCI World Index, 2090 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Communication Services	8.67	8.17	3.66	0.00	0.00	0.00
Consumer Discretionary	9.93	9.57	8.00	5.48	2.75	0.00
Consumer Staples	5.46	4.38	5.53	6.11	4.54	0.00
Energy	3.53	5.07	9.33	19.02	36.54	72.35
Financials	16.40	15.04	18.24	23.91	27.13	22.87
Health Care	9.97	4.60	3.77	5.57	5.97	0.00
Industrials	10.94	10.50	6.39	1.79	0.00	0.00
Information Technology	27.39	25.99	18.84	9.60	4.64	2.71
Materials	3.12	3.79	4.58	4.41	3.20	0.00
Real Estate	1.88	5.94	8.86	8.84	8.09	0.00
Utilities	2.70	6.95	12.79	15.26	7.14	2.07

Table 36: Sector allocation (in %) with constraints on $\mathcal{SE}$ (MSCI World Index, 2090 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Communication Services	8.67	9.10	9.19	8.72	6.46	1.48
Consumer Discretionary	9.93	9.07	8.10	6.52	4.01	0.25
Consumer Staples	5.46	4.66	4.11	1.54	0.40	0.02
Energy	3.53	2.64	2.13	0.52	0.00	0.01
Financials	16.40	22.00	28.55	44.17	61.62	84.74
Health Care	9.97	9.41	9.44	7.15	3.30	0.43
Industrials	10.94	10.07	8.03	3.82	1.70	3.82
Information Technology	27.39	27.62	27.74	26.68	22.50	9.24
Materials	3.12	2.05	0.92	0.21	0.00	0.01
Real Estate	1.88	1.76	1.04	0.49	0.00	0.01
Utilities	2.70	1.62	0.74	0.18	0.00	0.01

Table 37: Regional allocation (in %) with constraints on $\mathcal{PE}$ (MSCI World Index, 2090 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Canada	3.31	7.73	11.44	10.53	5.81	0.00
Europe	16.04	15.68	18.61	28.86	45.61	74.42
Japan	5.45	11.52	9.48	4.53	2.75	0.00
USA	72.38	62.26	56.74	52.15	45.83	25.58
Others	2.82	2.81	3.73	3.95	0.00	0.00

Table 38: Regional allocation (in %) with constraints on $\mathcal{SE}$ (MSCI World Index, 2090 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Canada	3.31	3.58	3.84	5.12	5.57	5.93
Europe	16.04	18.30	18.03	19.76	21.92	32.80
Japan	5.45	6.14	5.20	4.43	2.22	0.67
USA	72.38	68.41	69.66	66.54	65.93	56.56
Others	2.82	3.56	3.27	4.15	4.35	4.04

B.2 MSCI EM Index

Table 39: Statistics of the exposure and sensitivity scores (MSCI EM Index)

Metric	Statistic	Medium scenario			High scenario		
		2030	2050	2090	2030	2050	2090
$\mathcal{PE}$	Mean	60.8	66.6	72.7	62.4	71.2	82.7
	Q_1	57.0	63.0	69.0	66.0	74.0	85.0
	Q_3	65.0	70.0	76.0	58.0	68.0	81.0
	$Q_3 - Q_1$	8.0	7.0	7.0	8.0	6.0	4.0
$\mathcal{SE}$	Mean	37.3	42.0	47.3	38.5	45.9	57.4
	Q_1	26.0	30.5	35.0	49.0	57.0	71.0
	Q_3	47.6	53.0	59.0	27.0	34.0	45.0
	$Q_3 - Q_1$	21.6	22.5	24.0	22.0	23.0	26.0

Figure 15: Histograms of the exposure score $\mathcal{PE}$ (MSCI EM Index)

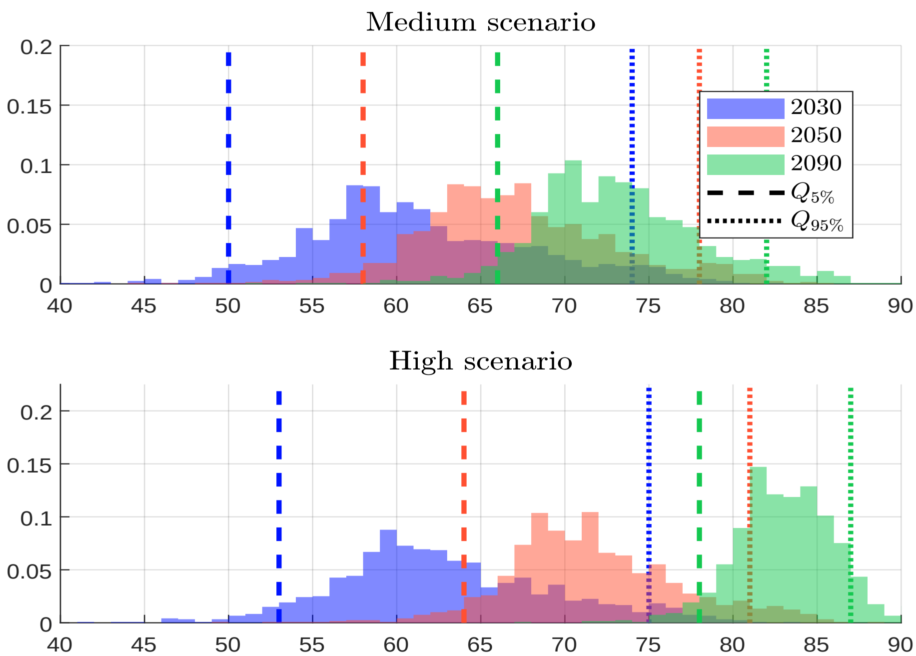


Figure 16: Histograms of the sensitivity score $\mathcal{SE}$ (MSCI EM Index)

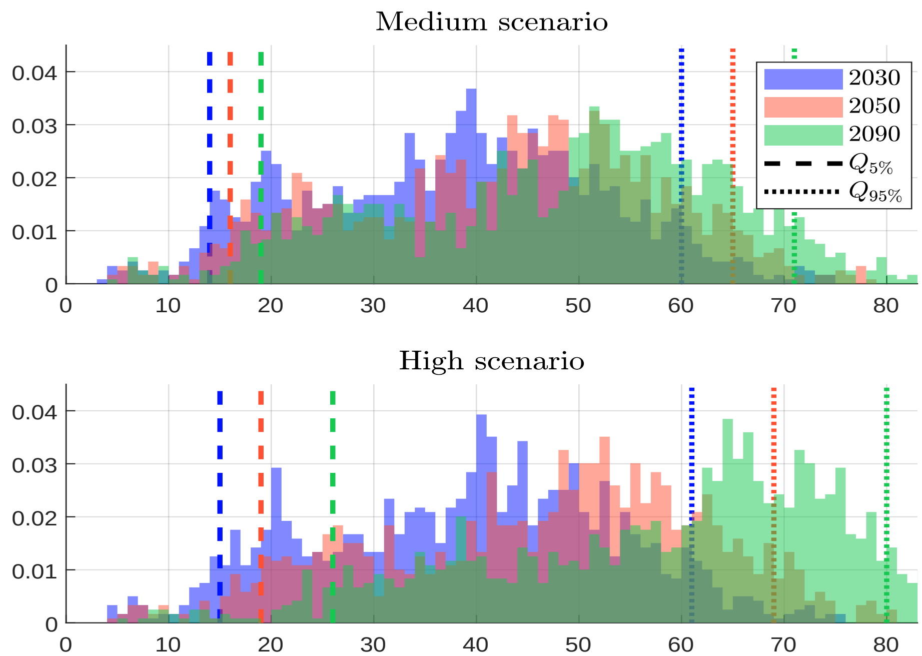


Figure 17: Boxplot of the exposure score $\mathcal{PE}$ per GICS sector (MSCI EM Index, 2030 medium scenario)

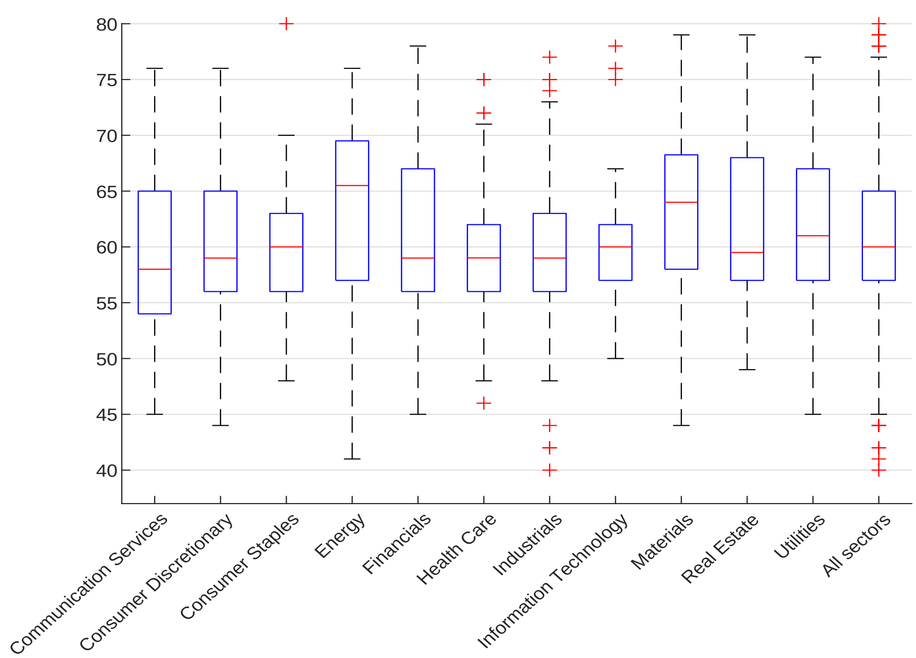


Figure 18: Boxplot of the sensitivity score $\mathcal{SE}$ per GICS sector (MSCI EM Index, 2030 medium scenario)

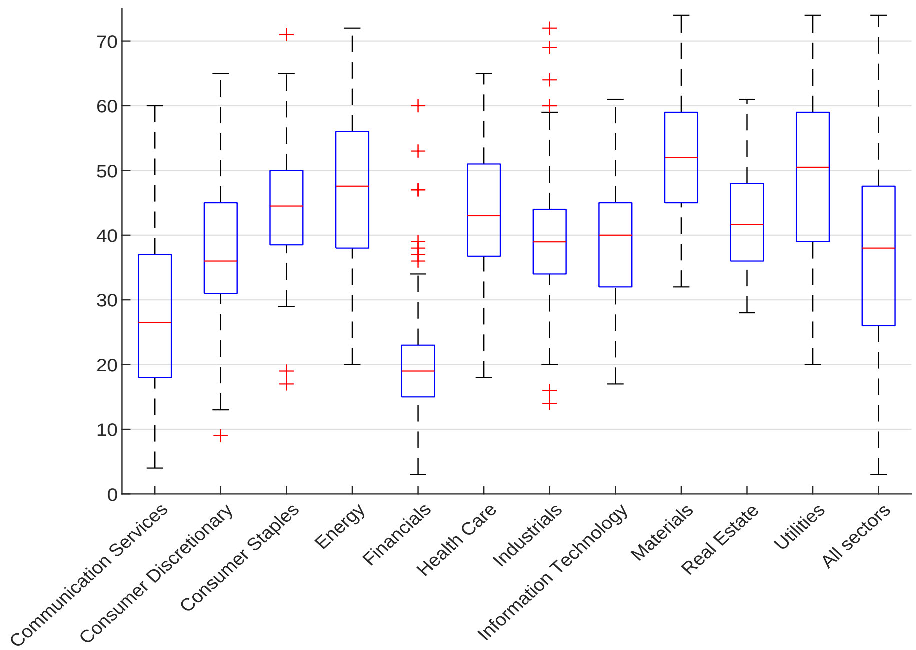


Table 40: Pearson correlation between physical risk and transition risk scores (MSCI EM Index, 2030 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	11.45	10.39	2.51	1.40	4.63
	p-value	0.01	0.03	38.49	62.94	10.97
High	$\rho(\mathcal{PE}, \mathcal{TR})$	11.65	10.53	2.77	1.13	4.44
	p-value	0.01	0.03	33.85	69.59	12.52
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	30.17	31.12	46.19	2.33	11.92
	p-value	0.00	0.00	0.00	42.02	0.00
High	$\rho(\mathcal{SE}, \mathcal{TR})$	29.76	31.10	46.34	2.26	11.75
	p-value	0.00	0.00	0.00	43.56	0.00

Table 41: Spearman correlation between physical risk and transition risk scores (MSCI EM Index, 2030 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	10.31	11.71	3.28	4.49	8.00
	p-value	0.04	0.00	25.67	12.10	0.56
High	$\rho(\mathcal{PE}, \mathcal{TR})$	10.59	11.45	3.59	4.69	8.36
	p-value	0.02	0.01	21.43	10.48	0.38
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	66.87	60.14	62.25	-14.76	10.57
	p-value	0.00	0.00	0.00	0.00	0.03
High	$\rho(\mathcal{SE}, \mathcal{TR})$	66.92	60.19	62.17	-14.80	10.64
	p-value	0.00	0.00	0.00	0.00	0.02

Table 42: Pearson correlation between physical risk and transition risk scores (MSCI EM Index, 2090 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	12.29	12.23	3.12	0.93	4.47
	p-value	0.00	0.00	28.08	74.88	12.26
High	$\rho(\mathcal{PE}, \mathcal{TR})$	12.13	14.01	5.81	−0.30	3.37
	p-value	0.00	0.00	4.44	91.76	24.35
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	27.42	30.10	46.55	1.83	10.72
	p-value	0.00	0.00	0.00	52.71	0.02
High	$\rho(\mathcal{SE}, \mathcal{TR})$	24.87	28.93	47.01	1.44	9.68
	p-value	0.00	0.00	0.00	61.97	0.08

Table 43: Spearman correlation between physical risk and transition risk scores (MSCI EM Index, 2090 medium and high scenarios)

Scenario	Statistic (in %)	$\mathcal{CI}_1$	$\mathcal{CI}_2$	$\mathcal{CI}_3^{\text{up}}$	$\mathcal{CI}_3^{\text{down}}$	$\mathcal{CI}_{1-3}$
Medium	$\rho(\mathcal{PE}, \mathcal{TR})$	14.06	12.89	4.36	5.61	10.13
	p-value	0.00	0.00	13.22	5.26	0.05
High	$\rho(\mathcal{PE}, \mathcal{TR})$	15.16	11.26	6.35	1.64	6.29
	p-value	0.00	0.01	2.81	57.13	2.97
Medium	$\rho(\mathcal{SE}, \mathcal{TR})$	66.83	60.35	62.08	−15.26	10.54
	p-value	0.00	0.00	0.00	0.00	0.03
High	$\rho(\mathcal{SE}, \mathcal{TR})$	66.79	60.30	63.25	−17.32	8.69
	p-value	0.00	0.00	0.00	0.00	0.26

Table 44: Weighted mean of climate risk measures per sector (MSCI EM Index, medium scenario)

Sector	n_j	b_j	$\mathcal{CI}_{1-3,j}$	$\mathcal{PE}_j^{2030}$	$\mathcal{SE}_j^{2030}$	$\mathcal{PE}_j^{2090}$	$\mathcal{SE}_j^{2090}$
Communication Services	58	9.5	111	57.3	18.9	70.7	25.6
Consumer Discretionary	117	12.0	943	62.0	33.1	73.1	42.4
Consumer Staples	84	3.8	563	60.7	42.9	72.4	53.8
Energy	48	3.9	6 751	62.9	47.1	73.7	57.2
Financials	246	22.2	2 242	62.5	19.9	73.5	27.2
Health Care	77	3.2	173	59.0	41.7	70.8	52.7
Industrials	172	7.1	5 901	59.6	39.0	71.7	49.9
Information Technology	169	27.7	383	61.4	43.2	72.7	53.7
Materials	129	6.9	2 989	64.4	52.9	75.5	63.3
Real Estate	34	1.4	627	64.5	42.3	75.5	52.9
Utilities	62	2.3	4 455	62.6	48.8	74.8	59.2

Table 45: Weighted mean of climate risk measures per region (MSCI EM Index, medium scenario)

Region	n_k	b_k	$\mathcal{CI}_{1-3,k}$	$\mathcal{PE}_k^{2030}$	$\mathcal{SE}_k^{2030}$	$\mathcal{PE}_k^{2090}$	$\mathcal{SE}_k^{2090}$
Africa	30	3.6	1 095	63.5	35.0	74.8	43.4
China	560	28.5	1 162	59.2	28.0	71.6	36.4
EM Europe	42	2.5	1 932	57.9	27.8	69.9	35.1
India	163	15.2	2 169	65.4	37.5	74.3	45.9
Latin America	85	7.4	2 270	58.6	33.6	72.3	44.5
Middle East	73	5.7	2 375	72.6	35.0	81.5	43.0
Others	243	37.1	1 896	60.4	40.4	72.2	50.8

Table 46: Weighted mean of climate risk measures per country (MSCI EM Index, medium scenario)

Country	n_k	b_k	$\mathcal{CI}_{1-3,k}$	$\mathcal{PE}_k^{2030}$	$\mathcal{SE}_k^{2030}$	$\mathcal{PE}_k^{2090}$	$\mathcal{SE}_k^{2090}$
Brazil	45.0	4.4	2 954	54.6	28.3	69.7	39.4
Chile	12.0	0.5	1 546	68.2	39.1	77.7	48.1
China	560.0	28.5	1 162	59.2	28.0	71.6	36.4
Colombia	3.0	0.1	1 837	57.2	32.0	74.8	46.4
Czech Republic	3.0	0.1	2 174	54.0	34.2	68.0	43.9
Egypt	3.0	0.1	1 598	78.8	53.2	82.6	58.9
Greece	8.0	0.6	2 676	69.8	25.7	79.2	31.6
Hungary	3.0	0.3	1 932	50.9	25.0	65.7	32.2
India	163.0	15.2	2 169	65.4	37.5	74.3	45.9
Indonesia	18.0	1.2	4 797	58.9	38.8	74.8	53.0
Korea	82.0	12.8	3 153	56.8	34.6	69.9	45.2
Kuwait	7.0	0.7	1 994	70.6	27.6	80.3	36.0
Malaysia	27.0	1.2	2 540	52.4	33.9	71.4	50.2
Mexico	22.0	1.9	1 082	61.9	41.9	74.1	52.7
Peru	3.0	0.3	1 452	75.9	47.8	86.4	57.9
Philippines	11.0	0.4	1 085	61.2	38.7	75.1	53.3
Poland	16.0	1.0	1 363	49.6	25.0	62.7	32.3
Qatar	13.0	0.7	2 445	70.1	34.7	79.9	43.3
Saudi Arabia	36.0	2.9	2 762	74.0	36.2	82.0	43.1
South Africa	27.0	3.5	1 083	63.1	34.5	74.6	43.0
Taiwan	86.0	20.5	944	63.3	44.7	73.6	54.4
Thailand	19.0	1.0	1 367	56.5	35.4	69.6	47.3
Turkey	12.0	0.4	2 237	68.4	37.7	78.4	45.8
United Arab Emirates	17.0	1.4	1 751	72.2	36.5	82.0	46.2

Table 47: Estimates $\hat{\beta}_j$ and $\hat{\beta}_k$ of the regression analysis (MSCI EM Index, medium scenario)

Sector	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$
Intercept (Fin/China)	$2\,119^{***}$	58.64^{***}	70.66^{***}	17.99^{***}	25.14^{***}
Communication Services	$-2\,146^{***}$	-0.94	-0.21	8.09^{***}	10.10^{***}
Consumer Discretionary	$-1\,142^{*}$	-0.22	0.15	18.13^{***}	21.92^{***}
Consumer Staples	$-1\,521^{**}$	0.31	0.77	26.06^{***}	30.61^{***}
Energy	$8\,126^{***}$	1.53^{*}	1.59^{**}	26.89^{***}	30.68^{***}
Health Care	$-2\,093^{***}$	-0.57	-0.23	23.37^{***}	27.18^{***}
Industrials	$1\,396^{**}$	-0.05	0.34	19.95^{***}	23.80^{***}
Information Technology	$-1\,945^{***}$	0.50	0.72^{*}	20.14^{***}	24.19^{***}
Materials	487	3.10^{***}	2.97^{***}	33.14^{***}	37.05^{***}
Real Estate	$-1\,458$	-0.31	0.19	22.14^{***}	26.42^{***}
Utilities	$2\,621^{***}$	1.93^{**}	2.62^{***}	30.50^{***}	34.31^{***}
Africa	-615	5.52^{***}	4.02^{***}	1.85	0.27
EM Europe	-761	0.43	-0.09	-0.51	-2.25
India	212	6.15^{***}	2.90^{***}	5.13^{***}	3.55^{***}
Latin America	$-1\,109^{*}$	-0.42	1.06^{**}	-3.15^{***}	-2.47^{**}
Middle East	-344	13.85^{***}	10.75^{***}	7.85^{***}	6.98^{***}
Others	$1\,118^{**}$	-0.47	0.22	0.99	1.82^{**}
R_c^2	12.47%	33.64%	31.42%	56.82%	57.51%

Table 48: Estimates $\hat{\beta}_k$ of the regression analysis using region dummies (MSCI EM Index, medium scenario)

Region	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$	$\mathcal{GI}$
Intercept (China)	1 907***	59.14***	71.41***	37.11***	47.51***	
Africa	−746	5.79***	4.19***	−1.08	−3.45	
EM Europe	−100	0.23	−0.31	−6.47***	−9.25***	
India	523	6.13***	2.88***	4.69***	2.98**	
Latin America	−445	−0.18	1.34***	−3.06*	−2.66	
Middle East	368	13.73***	10.59***	2.44	0.55	
Others	1 119**	−0.66	0.06	−0.86	−0.20	
$\bar{R}_c^2$	0.22%	31.58%	27.87%	2.25%	1.43%	

Table 49: Estimates $\hat{\beta}_k$ of the regression analysis using country dummies (MSCI EM Index, medium scenario)

Region	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$
Intercept (China)	1 907***	59.14***	71.41***	37.11***	47.51***
Brazil	−103	−4.63***	−1.41**	−8.98***	−8.27***
Chile	−690	8.44***	6.00***	4.81	3.65
Colombia	−296	−1.14	3.92*	−6.44	−2.85
Czech Republic	247	−5.81**	−4.08*	−9.78	−12.51
Egypt	−915	20.52***	11.92***	16.56**	11.49
Greece	−102	11.36***	8.21***	−7.61	−11.89**
Hungary	−288	−6.81**	−4.75**	−5.78	−6.85
India	523	6.13***	2.88***	4.69***	2.98**
Indonesia	4 407***	0.58	3.90***	5.95*	9.67**
Korea	2 207***	−3.67***	−3.11***	−4.55***	−4.94***
Kuwait	−276	12.00***	9.87***	−0.83	−1.80
Malaysia	148	−6.51***	0.03	−0.85	4.82
Mexico	−986	1.90*	2.13***	2.57	2.90
Peru	−775	17.86***	15.59***	16.22**	15.49*
Philippines	−735	4.13***	4.86***	3.80	7.12
Poland	−732	−8.85***	−8.14***	−9.99***	−12.90***
Qatar	925	13.16***	10.36***	3.58	2.03
Saudi Arabia	374	14.15***	10.15***	0.37	−2.86
South Africa	−727	4.15***	3.33***	−3.04	−5.10
Taiwan	239	3.50***	2.01***	0.94	−0.02
Thailand	−254	−2.04*	−1.47*	−2.22	−1.30
Turkey	703	8.19***	6.50***	−0.36	−2.43
United Arab Emirates	195	13.97***	12.00***	7.30**	7.61*
$\bar{R}_c^2$	−0.06%	49.83%	45.44%	4.58%	3.75%

Table 50: Estimates $\hat{\beta}_j$ and $\hat{\beta}_k$ of the regression analysis (MSCI EM Index, medium scenario)

Sector	$\mathcal{CI}_{1-3}$	$\mathcal{PE}^{2030}$	$\mathcal{PE}^{2090}$	$\mathcal{SE}^{2030}$	$\mathcal{SE}^{2090}$
Intercept (Fin/China)	2 144***	58.77***	70.63***	17.89***	24.86***
Communication Services	−2 125**	−0.61	−0.08	8.42***	10.29***
Consumer Discretionary	−1 178*	−0.26	0.25	18.36***	22.33***
Consumer Staples	−1 568**	0.59	0.93**	26.05***	30.51***
Energy	8 110***	2.17***	1.93***	27.30***	30.91***
Health Care	−2 107***	−0.28	0.16	24.00***	28.05***
Industrials	1 304**	0.03	0.60*	20.31***	24.44***
Information Technology	−1 967***	−0.48	0.45	19.94***	24.68***
Materials	411	2.79***	2.78***	33.06***	37.10***
Real Estate	−1 278	−1.42	−0.54	20.62***	24.83***
Utilities	2 723***	2.83***	2.94***	31.05***	34.40***
Brazil	−1 290	−5.28***	−1.83***	−8.15***	−6.67***
Chile	−1 124	7.99***	5.70***	4.70*	4.02
Colombia	−1 440	−1.71	3.72*	2.43	8.34
Czech Republic	−897	−6.38**	−4.28**	−0.91	−1.33
Egypt	−203	21.17***	12.57***	20.22***	15.69***
Greece	−119	11.52***	8.57***	2.09	−0.40
Hungary	−2 526	−7.07***	−4.66**	−3.66	−3.85
India	210	6.03***	2.86***	5.11***	3.62***
Indonesia	2 949**	−0.24	3.38***	4.59**	8.75***
Korea	1 907***	−3.42***	−2.88***	−2.77**	−3.07**
Kuwait	−27	12.66***	10.74***	14.25***	15.84***
Malaysia	103	−6.76***	−0.08	0.74	7.05***
Mexico	−721	1.80*	2.07***	−0.25	−0.27
Peru	−1 286	16.37***	14.51***	13.40**	13.41**
Philippines	−1 042	4.57***	5.29***	8.47***	12.50***
Poland	−1 203	−8.95***	−8.03***	−4.98**	−6.82***
Qatar	−640	12.93***	10.40***	9.87***	9.84***
Saudi Arabia	84	14.03***	10.21***	4.50***	2.30
South Africa	−668	3.75***	3.17***	−0.01	−1.08
Taiwan	975	3.93***	2.27***	3.35***	2.30*
Thailand	−652	−2.08*	−1.39*	−0.94	0.41
Turkey	−164	8.17***	6.65***	4.35	3.19
United Arab Emirates	−1 297	14.11***	12.26***	11.19***	12.29***
$\bar{R}_c^2$	11.91%	52.44%	49.02%	59.56%	60.40%

Table 51: Overlap (in %) between transition and physical risk-managed tracking portfolios (MSCI EM Index, 2090 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=5\%$	$\mathcal{R}=10\%$	$\mathcal{R}=15\%$	$\mathcal{R}=20\%$	$\mathcal{R}=25\%$
	$\mathcal{R}=0\%$	100.0	68.3	38.8	18.6	3.2	0.4
	$\mathcal{R}=20\%$	92.1	69.7	39.0	18.6	3.1	0.4
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	93.2	69.1	38.7	18.5	3.1	0.4
	$\mathcal{R}=60\%$	83.0	66.8	38.0	17.9	2.7	0.4
	$\mathcal{R}=80\%$	66.3	59.4	36.6	17.1	2.2	0.4
		$\mathcal{SE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=10\%$	$\mathcal{R}=20\%$	$\mathcal{R}=40\%$	$\mathcal{R}=60\%$	$\mathcal{R}=80\%$
	$\mathcal{R}=0\%$	100.0	86.1	74.9	49.5	24.1	8.0
	$\mathcal{R}=20\%$	92.1	87.1	74.8	49.4	23.9	7.7
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	93.2	86.1	74.6	49.2	24.0	7.9
	$\mathcal{R}=60\%$	83.0	79.3	70.0	47.3	23.8	8.2
	$\mathcal{R}=80\%$	66.3	64.5	59.8	42.5	24.2	9.0

Table 52: Correlation (in %) between transition and physical risk-managed tracking portfolios (MSCI EM Index, 2030 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=5\%$	$\mathcal{R}=10\%$	$\mathcal{R}=15\%$	$\mathcal{R}=20\%$	$\mathcal{R}=25\%$
	$\mathcal{R}=0\%$	100.0	100.0	99.7	99.0	96.3	89.8
	$\mathcal{R}=20\%$	100.0	100.0	99.8	99.0	96.4	89.8
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	100.0	100.0	99.7	99.0	96.3	89.7
	$\mathcal{R}=60\%$	100.0	99.9	99.7	99.0	96.3	89.7
	$\mathcal{R}=80\%$	99.9	99.8	99.7	98.9	96.2	89.5
		$\mathcal{SE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=10\%$	$\mathcal{R}=20\%$	$\mathcal{R}=40\%$	$\mathcal{R}=60\%$	$\mathcal{R}=80\%$
	$\mathcal{R}=0\%$	100.0	100.0	99.9	99.6	97.6	90.2
	$\mathcal{R}=20\%$	100.0	100.0	99.9	99.6	97.6	90.2
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	100.0	100.0	99.9	99.6	97.6	90.2
	$\mathcal{R}=60\%$	100.0	100.0	99.9	99.6	97.6	90.3
	$\mathcal{R}=80\%$	99.9	99.9	99.8	99.5	97.6	90.3

Table 53: Correlation (in %) between transition and physical risk-managed tracking portfolios (MSCI EM Index, 2090 medium scenario)

		$\mathcal{PE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=5\%$	$\mathcal{R}=10\%$	$\mathcal{R}=15\%$	$\mathcal{R}=20\%$	$\mathcal{R}=25\%$
	$\mathcal{R}=0\%$	100.0	99.9	98.7	93.9	80.7	53.8
	$\mathcal{R}=20\%$	100.0	99.9	98.7	93.9	80.8	53.9
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	100.0	99.9	98.7	93.9	80.7	53.8
	$\mathcal{R}=60\%$	100.0	99.8	98.7	93.8	80.7	53.8
	$\mathcal{R}=80\%$	99.9	99.8	98.6	93.7	80.6	53.7
		$\mathcal{SE}$					
		$\mathcal{R}=0\%$	$\mathcal{R}=10\%$	$\mathcal{R}=20\%$	$\mathcal{R}=40\%$	$\mathcal{R}=60\%$	$\mathcal{R}=80\%$
	$\mathcal{R}=0\%$	100.0	100.0	99.9	99.5	97.3	88.5
	$\mathcal{R}=20\%$	100.0	100.0	99.9	99.5	97.3	88.5
$\mathcal{CI}_{1-3}$	$\mathcal{R}=40\%$	100.0	100.0	99.9	99.5	97.3	88.5
	$\mathcal{R}=60\%$	100.0	100.0	99.9	99.5	97.3	88.6
	$\mathcal{R}=80\%$	99.9	99.9	99.8	99.4	97.3	88.6

Table 54: Number of invested stocks (MSCI EM Index)

$\mathcal{R}$	$\mathcal{CI}$	$\mathcal{PE}$				$\mathcal{SE}$			
		Medium		High		Medium		High	
		2030	2090	2030	2090	2030	2090	2030	2090
0%	1 196	1 196	1 196	1 196	1 196	1 196	1 196	1 196	1 196
5%	1 196	1 115	1 167	1 194	447	1 196	1 196	1 196	1 196
10%	1 196	1 196	296	1 196	72	1 196	1 196	1 196	1 196
15%	1 196	536	211	296	5	1 196	1 196	1 196	1 196
20%	1 196	156	38	104		1 196	1 196	1 196	1 196
25%	1 195	109	7	55		874	1 196	1 196	1 196
40%	1 191	2				346	1 056	625	924
60%	1 160					144	177	229	118
80%	782					44	32	38	28

Table 55: Sector allocation (in %) with constraints on $\mathcal{CI}_{1-3}$ (MSCI EM Index)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Communication Services	9.51	9.18	9.34	10.18	11.93	15.57
Consumer Discretionary	12.04	12.11	12.18	12.47	12.95	12.69
Consumer Staples	3.75	3.72	3.82	4.45	5.63	6.65
Energy	3.92	3.47	3.35	2.89	2.01	1.17
Financials	22.24	20.13	20.37	20.40	16.44	10.03
Health Care	3.25	3.59	3.64	4.10	5.77	9.24
Industrials	7.09	8.02	7.74	6.78	5.81	4.08
Information Technology	27.67	28.44	28.52	28.87	30.64	33.21
Materials	6.86	7.31	7.15	6.32	4.87	3.17
Real Estate	1.36	1.53	1.53	1.64	2.04	2.02
Utilities	2.32	2.50	2.35	1.90	1.91	2.15

Table 56: Sector allocation (in %) with constraints on $\mathcal{PE}$ (MSCI EM Index, 2030 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Communication Services	9.51	9.66	10.44	10.91	10.51	8.60
Consumer Discretionary	12.04	11.62	11.28	10.59	8.08	7.99
Consumer Staples	3.75	4.32	4.73	4.96	3.43	0.99
Energy	3.92	3.43	3.60	5.65	8.56	11.53
Financials	22.24	21.72	19.82	19.60	18.62	16.85
Health Care	3.25	3.71	3.76	3.80	5.46	7.48
Industrials	7.09	8.17	10.14	12.58	18.40	25.79
Information Technology	27.67	27.72	25.70	20.97	14.32	6.20
Materials	6.86	5.79	5.70	5.24	5.11	6.26
Real Estate	1.36	1.22	1.45	1.19	0.80	0.28
Utilities	2.32	2.66	3.39	4.51	6.71	8.02

Table 57: Sector allocation (in %) with constraints on $\mathcal{SE}$ (MSCI EM Index, 2030 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Communication Services	9.51	9.62	9.77	10.73	15.06	18.16
Consumer Discretionary	12.04	11.45	10.65	8.53	6.48	2.94
Consumer Staples	3.75	2.44	1.34	0.39	0.60	0.00
Energy	3.92	2.69	1.60	0.09	0.00	0.00
Financials	22.24	29.76	39.12	58.90	70.05	78.88
Health Care	3.25	2.72	2.06	0.56	0.00	0.00
Industrials	7.09	6.81	5.37	1.67	0.57	0.01
Information Technology	27.67	27.43	25.84	18.80	7.23	0.01
Materials	6.86	4.57	2.62	0.12	0.00	0.00
Real Estate	1.36	1.05	0.68	0.04	0.00	0.00
Utilities	2.32	1.46	0.97	0.16	0.00	0.00

Table 58: Sector allocation (in %) with constraints on $\mathcal{PE}$ (MSCI EM Index, 2090 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Communication Services	9.51	9.58	9.96	10.43	6.94	5.41
Consumer Discretionary	12.04	11.65	9.69	6.68	8.26	15.56
Consumer Staples	3.75	3.73	3.08	2.85	2.93	0.00
Energy	3.92	4.02	7.10	9.83	9.78	2.31
Financials	22.24	21.60	21.94	21.18	21.95	2.38
Health Care	3.25	4.30	4.51	6.94	8.67	0.00
Industrials	7.09	9.27	14.31	23.69	33.51	74.34
Information Technology	27.67	26.68	20.14	10.87	0.34	0.00
Materials	6.86	5.41	5.64	6.47	7.62	0.00
Real Estate	1.36	1.58	1.50	0.22	0.00	0.00
Utilities	2.32	2.17	2.12	0.85	0.00	0.00

Table 59: Sector allocation (in %) with constraints on $\mathcal{SE}$ (MSCI EM Index, 2090 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Communication Services	9.51	9.52	9.71	11.14	14.93	15.41
Consumer Discretionary	12.04	11.34	10.45	8.25	6.76	3.37
Consumer Staples	3.75	2.27	1.22	0.57	0.72	0.00
Energy	3.92	2.56	1.54	0.10	0.00	0.00
Financials	22.24	30.84	40.89	59.91	70.65	81.22
Health Care	3.25	2.64	1.89	0.42	0.01	0.00
Industrials	7.09	6.62	4.93	1.35	0.19	0.00
Information Technology	27.67	27.27	25.40	17.81	6.72	0.00
Materials	6.86	4.49	2.52	0.20	0.01	0.00
Real Estate	1.36	1.04	0.62	0.09	0.00	0.00
Utilities	2.32	1.40	0.83	0.14	0.01	0.00

Table 60: Regional allocation (in %) with constraints on $\mathcal{CI}_{1-3}$ (MSCI EM Index)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Africa	3.63	3.37	3.42	3.66	3.74	3.62
China	28.52	34.51	33.81	31.39	32.82	34.78
EM Europe	2.47	2.32	2.34	2.36	2.07	1.91
India	15.24	13.21	13.54	14.63	15.01	14.47
Latin America	7.37	6.81	6.92	7.24	6.74	5.69
Middle East	5.72	4.58	4.73	5.04	3.85	3.40
Others	37.05	35.20	35.24	35.68	35.77	36.14

Table 61: Regional allocation (in %) with constraints on $\mathcal{PE}$ (MSCI EM Index, 2030 medium scenario)

$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Africa	3.63	3.11	1.83	0.75	0.00	0.00
China	28.52	33.95	36.59	34.64	34.93	36.83
EM Europe	2.47	3.13	5.28	8.46	11.59	12.17
India	15.24	10.02	2.82	1.49	0.66	0.27
Latin America	7.37	8.30	8.15	6.45	8.73	12.85
Middle East	5.72	0.97	0.20	0.02	0.00	0.00
Others	37.05	40.52	45.13	48.20	44.09	37.89

Table 62: Regional allocation (in %) with constraints on $\mathcal{SE}$ (MSCI EM Index, 2030 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Africa	3.63	3.67	3.83	4.45	6.57	8.24
China	28.52	33.45	36.24	42.70	43.06	29.23
EM Europe	2.47	2.72	3.20	4.57	4.99	2.09
India	15.24	12.15	10.89	8.54	6.34	12.74
Latin America	7.37	7.04	6.40	5.57	7.22	14.46
Middle East	5.72	5.09	4.77	3.60	3.59	1.91
Others	37.05	35.88	34.68	30.57	28.22	31.34

Table 63: Regional allocation (in %) with constraints on $\mathcal{PE}$ (MSCI EM Index, 2090 medium scenario)

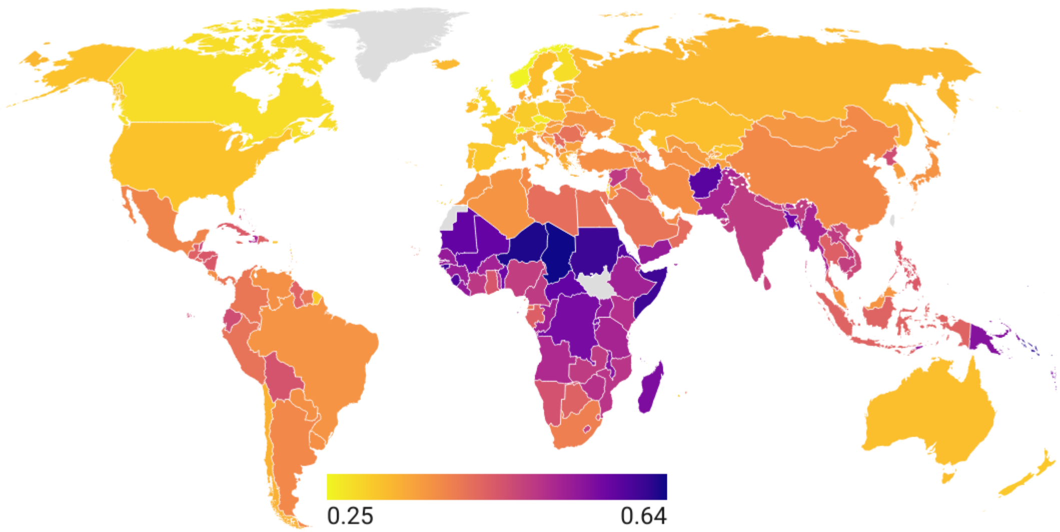
$\mathcal{R}$	0%	5%	10%	15%	20%	25%
Africa	3.63	2.13	1.13	0.01	0.00	0.00
China	28.52	39.64	39.23	38.36	39.71	47.71
EM Europe	2.47	5.28	13.11	19.83	22.94	7.79
India	15.24	7.79	2.66	0.09	0.00	0.00
Latin America	7.37	7.05	5.32	6.75	4.20	0.00
Middle East	5.72	0.11	0.00	0.01	0.00	0.00
Others	37.05	37.99	38.55	34.95	33.15	44.50

Table 64: Regional allocation (in %) with constraints on $\boldsymbol{\mathcal{SE}}$ (MSCI EM Index, 2090 medium scenario)

$\mathcal{R}$	0%	10%	20%	40%	60%	80%
Africa	3.63	3.72	3.94	4.55	6.78	9.42
China	28.52	34.32	36.86	43.28	41.22	26.51
EM Europe	2.47	2.88	3.55	5.47	6.35	2.72
India	15.24	12.18	11.07	7.72	6.59	14.98
Latin America	7.37	6.69	5.88	4.87	6.30	15.02
Middle East	5.72	5.18	5.01	4.17	4.18	1.43
Others	37.05	35.04	33.68	29.95	28.59	29.92

B.3 Strategic asset allocation

Figure 19: ND-GAIN vulnerability score (2023)



Source: ND-GAIN (2025) & Authors' calculations (created by Datawrapper).

Figure 20: Mean-variance efficient frontier (Portfolio #2, $\mathcal{R} = 10\%$)

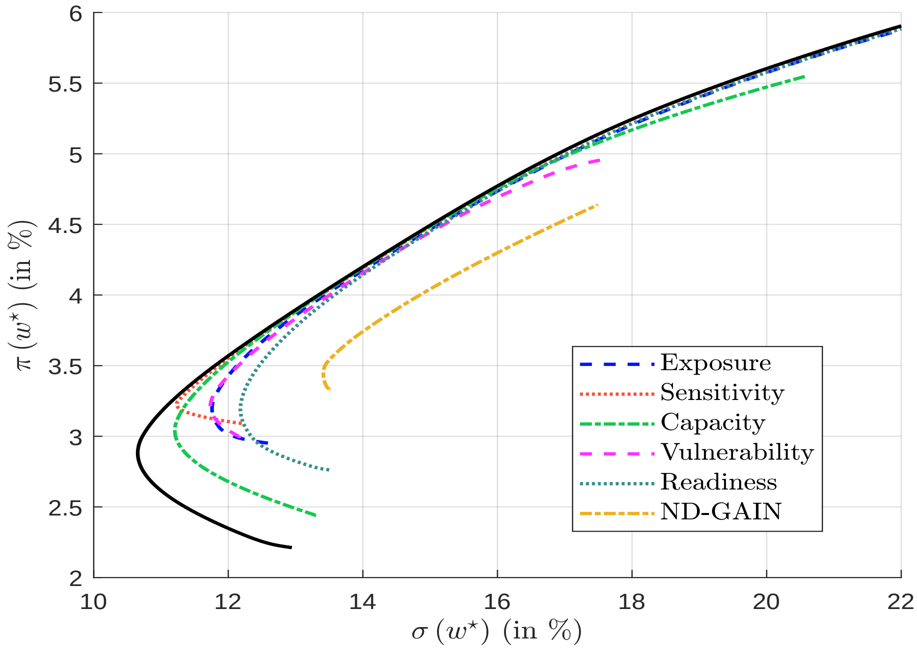


Figure 21: Mean-variance efficient frontier (Portfolio #3, $\mathcal{R} = 10\%$)

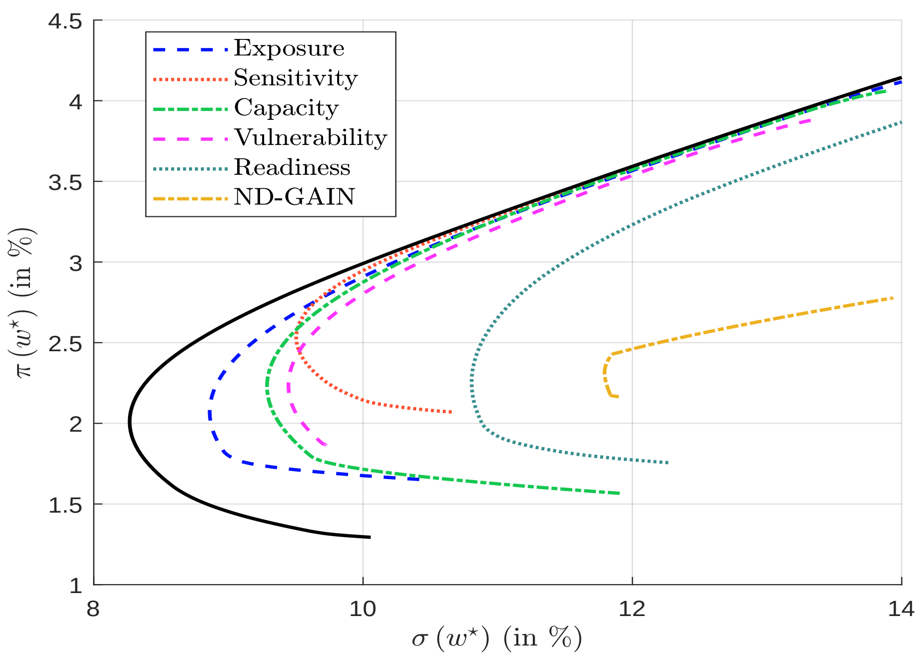


Figure 22: Mean-variance efficient frontier (Portfolio #4, $\mathcal{R} = 10\%$)

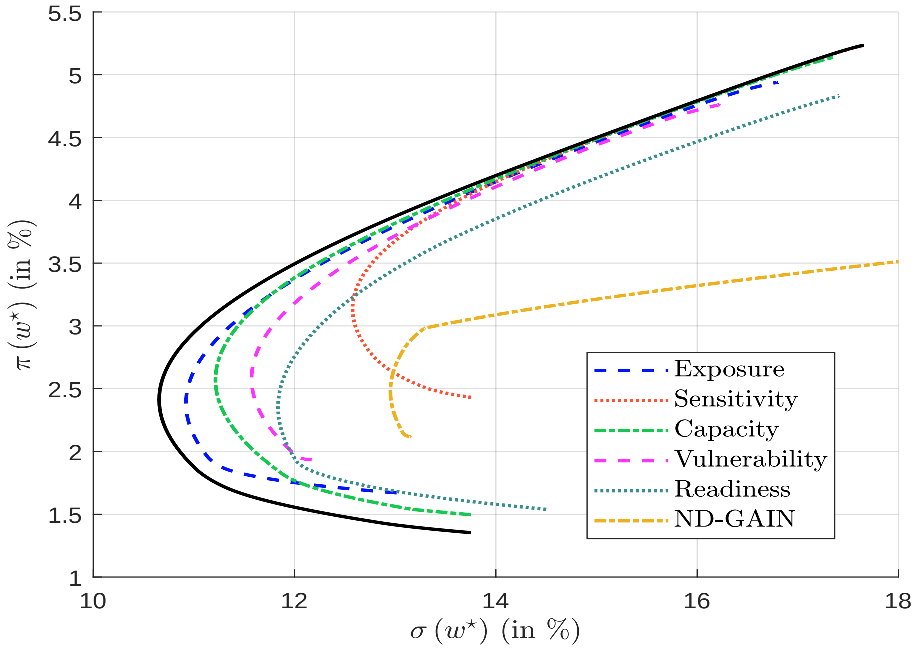


Figure 23: Mean-variance efficient frontier (Portfolio #5, $\mathcal{R} = 10\%$)

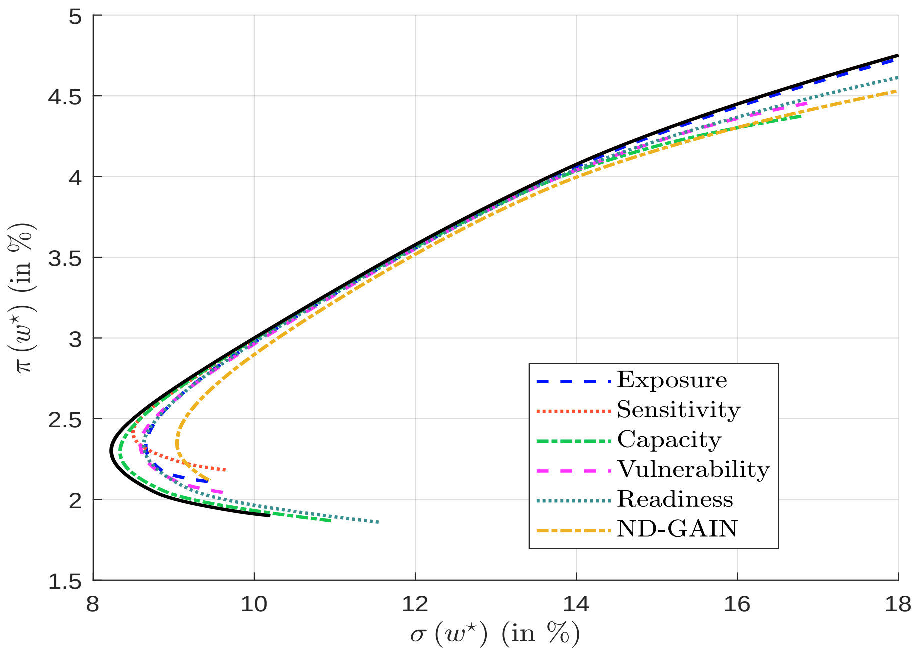


Figure 24: Mean-variance efficient frontier (Portfolio #6, $\mathcal{R} = 10\%$)

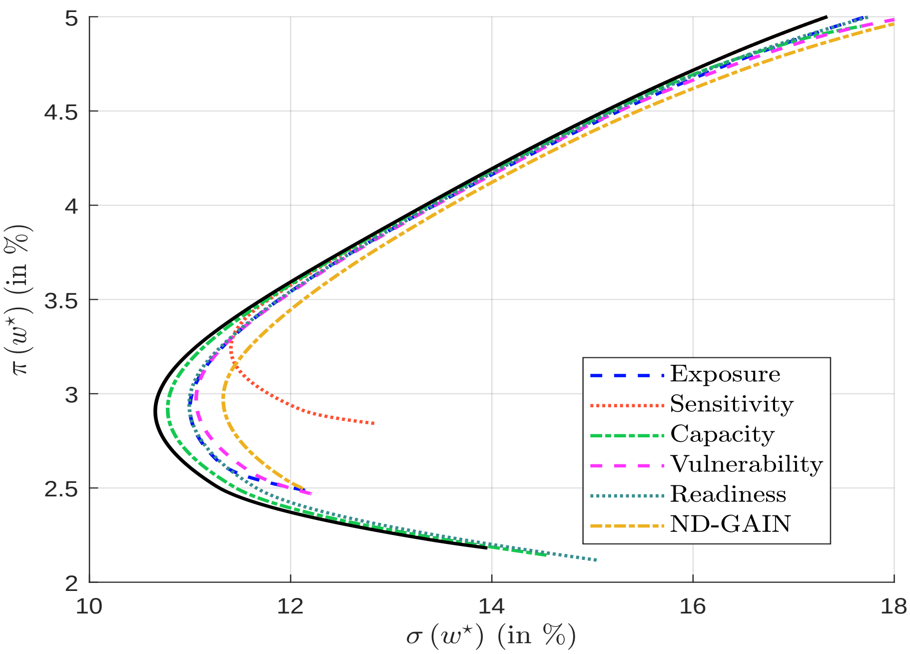


Figure 25: Financial cost $\mathcal{C}_{ost}(\mathcal{R})$ of physical risk (Portfolio #2)

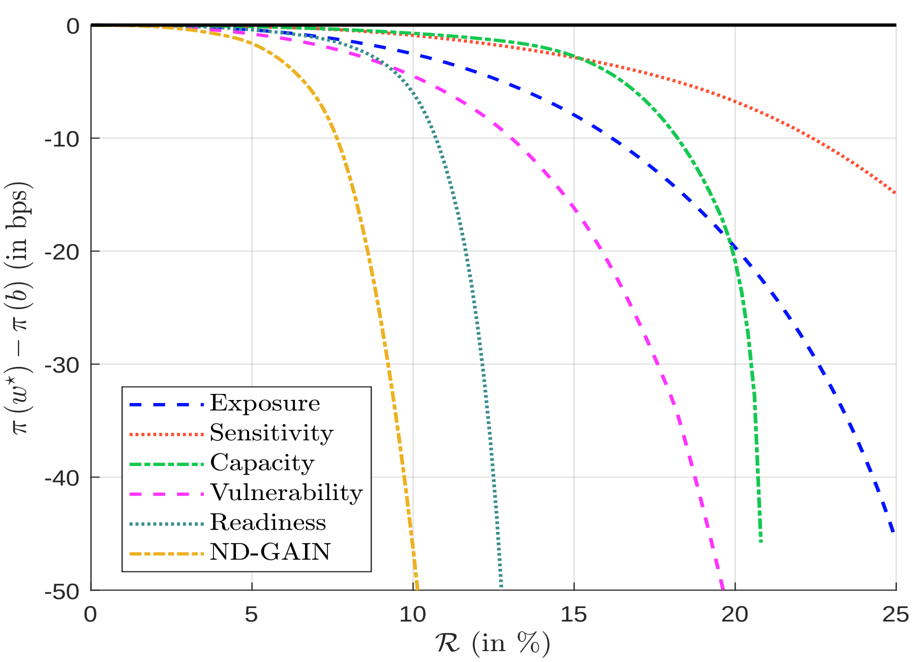


Figure 26: Financial cost $\mathcal{C}_{ost}(\mathcal{R})$ of physical risk (Portfolio #3)

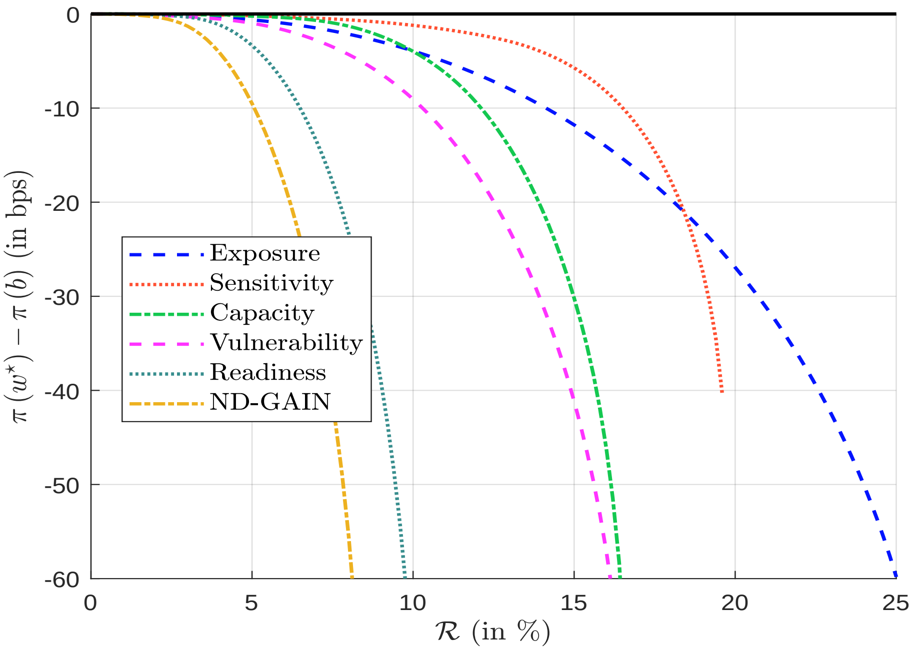


Figure 27: Financial cost $\mathcal{C}_{ost}(\mathcal{R})$ of physical risk (Portfolio #4)

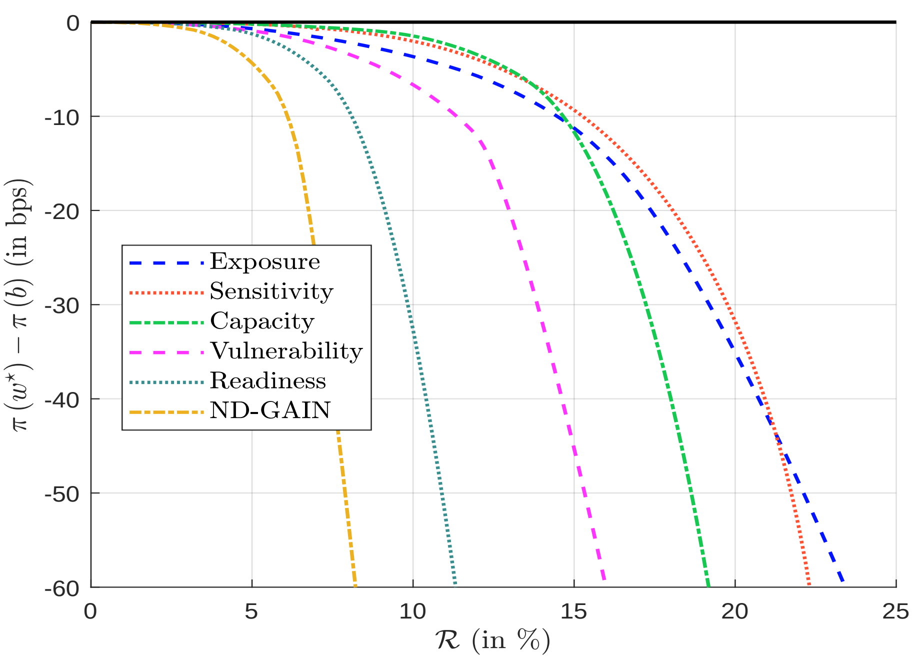


Figure 28: Financial cost $\mathcal{C}_{ost}(\mathcal{R})$ of physical risk (Portfolio #5)

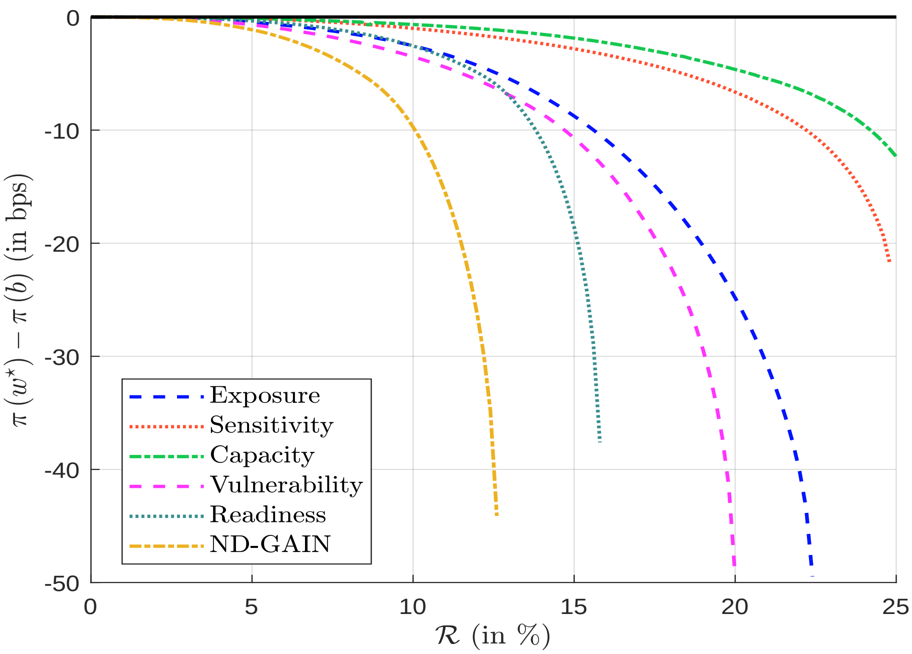
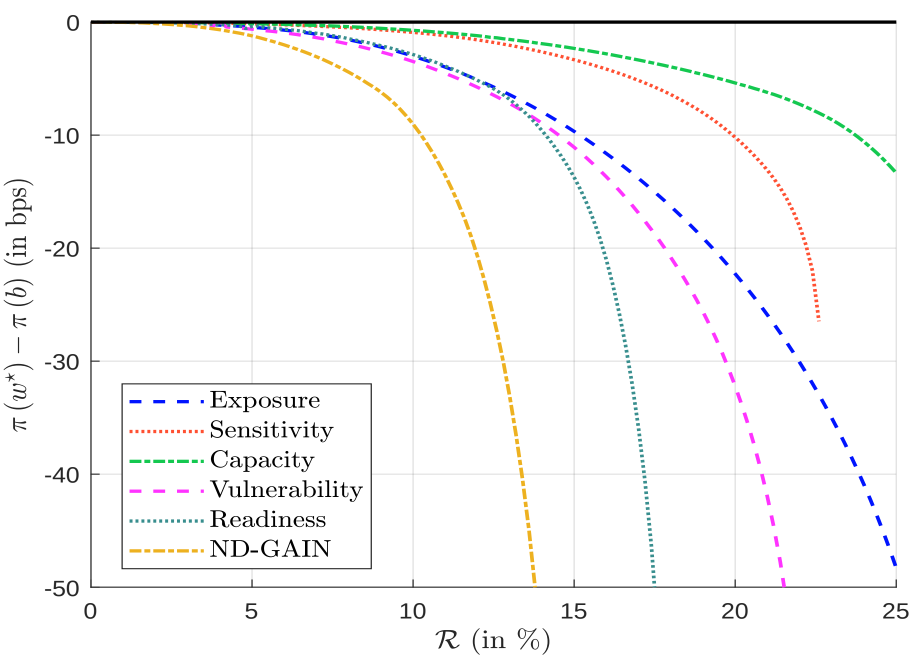


Figure 29: Financial cost $\mathcal{C}_{ost}(\mathcal{R})$ of physical risk (Portfolio #6)



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