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Introduction

I am delighted to introduce the latest Scientific Portfolio special issue of the EDHEC Research Insights supplement to Investment & Pensions Europe (IPE), which aims to provide institutional investors with an academic research perspective on the most relevant issues in the industry today.

We first look at climate transition risks in portfolio management by introducing a model that integrates firm-specific 'green' revenues, aligned with the European taxonomy. The analysis highlights three main results: revenue impacts are as influential as carbon pricing in shaping transition risks; effects vary within sectors, with some firms benefiting under ambitious transition scenarios; and socio-economic uncertainty strongly influences loss estimates.

Understanding the drivers influencing greenhouse gas emissions in financial portfolios is crucial for constructing and monitoring climate investment strategies. We compare existing frameworks for identifying the drivers of portfolio decarbonisation, exploring key drivers and methods to isolate their effects. Building on this review, a flexible three-step model is formalised to integrate these drivers, and five specific models are developed to address climate-related questions.

We examine the informational overlap between environmental, social and governance (ESG) scores and ESG exclusionary screening strategies within equity portfolios. While ESG scores are widely used for integrating sustainability considerations in portfolio management, they may not fully align with exclusion criteria targeting companies engaged in controversial activities or behaviour. By comparing the results of both approaches on a set of 417 indices, the analysis reveals that reliance on ESG scores alone omits a substantial proportion of companies that fail to meet 'do no harm' criteria.

Exclusion/negative screening is the most popular methodology used to integrate ESG criteria into investment strategies. We examine the impact of exclusion policies on the financial risks of 493 indices from Developed Europe and the US. To address varying ESG criteria, we built three screens: one based on consensual criteria among asset owners, another incorporating additional climate criteria, and a third eliminating companies negatively impacting any United Nations sustainable development goal. The first two screens show limited impact on index risks, especially when using optimised reallocation.

Finally, we look at the benefits of risk-based diversification for equity investors. Diversification benefits can be achieved while maintaining the level of active risk, an important feature for investors seeking to both fully utilise their active risk budget and manage extreme losses, and risk-based diversification is achievable without reducing expected long-term returns.

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

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

Beyond carbon price: a scenario-based quantification of portfolio financial loss from climate transition risks

Thomas Lorans, Deputy Head of ESG Research, Scientific Portfolio; **Julien Priol**, ESG Researcher, Scientific Portfolio; **Vincent Bouchet**, Director of ESG Research, Scientific Portfolio

This article (a summary of a recent research paper[1]) addresses climate transition risks in portfolio management by introducing a model that integrates firm-specific 'green' revenues, aligned with the European taxonomy, with economic and energy variables from adverse transition scenarios. Unlike short-term climate stress tests focusing on carbon pricing, our model incorporates operational cost and revenue transmission channels to derive a *conditional transition loss* metric. Applied to 1,287 listed companies, our analysis highlights significant portfolio equity risks with aggregate portfolio impacts ranging from 0.5-6% and sector-specific losses as high as 10-60% in vulnerable sectors such as utilities. Integrating such forward-looking scenario analysis results with backward-looking financial factor models may help capture shifts in investor perceptions and enhance equity portfolio risk management.

Key takeaways:

Climate transition risks present significant challenges for portfolio management. Short-term climate stress tests focus predominantly on carbon pricing and operational costs, often neglecting longer-term revenue impacts from demand changes.

This paper introduces a model combining firm-specific 'green' revenues, aligned with the European taxonomy, with economic and energy variables from adverse transition scenarios to calculate a *conditional transition loss* metric, capturing the interplay between revenue and cost dynamics.

Applied to the 1,287 MSCI World Index constituents, the analysis highlights three main results: revenue impacts are as influential as carbon pricing in shaping transition risks; effects vary within sectors, with some firms benefiting under ambitious transition scenarios; and socio-economic uncertainty strongly influences loss estimates.

Introduction

Climate-related transition risks are increasingly central to equity portfolio management. These risks pose potential disruptions while offering opportunities for firms aligned with climate goals. For equity portfolio managers, transition risks affect valuations, sectoral dynamics and risk-return profiles. Understanding and quantifying these risks is crucial for portfolio allocation. However, the pricing of transition risks in financial markets remains inconsistent.

Some research indicates firms with higher greenhouse gas emissions trade at a discount due to a carbon risk premium (Bolton and Kacperczyk [2023]). Others suggest green stocks have outperformed brown stocks, indicating transition risks are not uniformly priced (Bernardini et al [2021], Bauer et al [2022]). Differences between realised and expected returns, as well as structural barriers like inadequate risk models and short-term investment horizons, contribute to this uncertainty (Thomä and Chenet [2017], Campiglio et al [2023]).

Long-term scenario analysis has emerged as a critical tool for assessing transition risks. Unlike short-term climate stress tests focused on carbon pricing and operational cost impacts, scenario-based methodologies incorporate broader economic and energy transformations. Regulatory bodies like the Network for Greening the Financial System (NGFS) have advanced integrated assessment models to capture direct and indirect effects. However, these approaches often lack firm-level granularity, making it difficult to differentiate risks within sectors.

1 Lorans, T., J. Priol and V. Bouchet (2025). *Beyond Carbon Price: A Scenario-Based Quantification of Portfolio Financial Loss from Climate Transition Risks.* Scientific Portfolio Publication.

This paper introduces a model integrating firm-specific revenue data, particularly 'green' revenues aligned with the European taxonomy, alongside carbon intensity metrics. By linking firm revenue dependencies to sectoral variables from NGFS scenarios, the model captures both revenue and operational cost transmission channels, offering a more comprehensive transition risk framework. Additionally, it evaluates financial outcome sensitivity to scenario assumptions, time horizons, and model uncertainties.

Applying this approach to 1,287 MSCI World Index companies, the analysis finds revenue transmission effects as significant as carbon pricing in shaping transition risks. It highlights substantial intra-sectoral variation, with some firms benefiting while others face losses. Scenario and time horizon assumptions prove crucial, whereas the choice of an integrated assessment model has a more limited impact.

The rest of the paper is structured as follows: the first section introduces the model and data, the second section examines revenue transmission, sectoral differences and scenario sensitivity, and the third discusses findings in context, offering recommendations for future research and risk management.

Model and data

Equity asset prices can fluctuate due to shifts in investors' perceptions of the firm's future expected cash flows or changes in the discount rate applied to the present value of those cash flows (Pástor et al [2021]). Transition risk drivers can influence these cash flows, potentially harming 'brown' firms or benefiting 'green' firms. This section introduces a model and its calibration for the *conditional transition loss* in equity value caused by changes in expectations surrounding climate transition scenarios, focusing on the impact of changes in expected cash flows.

A discounted-cash flow model for transition risk channels

The analysis uses a discounted cash flow model that captures two key transmission channels. The first channel, revenue, varies across firms based on activity contributions, with each segment driven by a corresponding scenario variable. The second channel, operating costs, depends on the firm's direct emissions (Scope 1) intensity and the carbon price specified in the scenario.

Let $CF_{i,t}$ denote the cash flows of firm i at time t, under the expected (*baseline*) transition scenario. We assume the following cash flow structure:

$$CF_{i,t} = Y_{i,t}\left(1-\omega_{i,t}-\theta-\tau-\rho\right)$$

where $Y_{i,t}$ represents revenue, $\omega_{i,t}$ the carbon costs rate, θ the operating cost rate, τ is the tax rate, and ρ the (net) investments rate.[2] Firm revenue, $Y_{i,t}$, is the sum of the revenue of its activity segments, denoted by s. The revenue dynamic is driven by a growth factor specific to each activity segment:

$$Y_{i,t} = \sum_s Y_{i,s,0} \times \frac{Y_{s,t}}{Y_{s,0}}$$

where $Y_{i,s,0}$ is the initial sales of product s for stock i, and $Y_{s,t}/Y_{s,0}$ is the growth factor of the product's demand over time, determined by the scenario.

The carbon cost rate is modelled as the product of a firm's direct emissions (Scope 1) and the scenario's carbon price, excluding indirect emissions (Scope 2 and 3) from direct cost calculations. This assumes their impact is already factored in at the sector level via the integrated assessment model and reflected in firm cash flows through the revenue channel.

Finally, to avoid negative cash flows, the carbon cost rate is capped such that the sum of the carbon cost rate, tax rate, operating cost rate, and investment rate does not exceed 1:

$$\omega_{i,t} = \min\left(\sigma_i \times \Lambda_t, 1-\tau-\theta-\rho\right)$$

where σ_i is the carbon intensity of the stock i and Λ_t is the carbon price.

Once the cash flows are projected between the reference date and the analysis horizon, they are discounted by weighted average cost of capital (WACC):

$$DCF_{i,t} = \frac{CF_{i,t}}{\left(1+WACC\right)^t}$$

These discounted cash flows are summed to compute the total firm value V_i:

$$V_i = \sum_t^T DCF_{i,t}$$

The *conditional transition loss* is finally computed as the relative change in the stock value compared to the value in the baseline scenario:

$$L_i = -\left(\frac{\Delta V_i}{V_i^{baseline}}\right)$$

Decomposing the revenue and carbon cost effects on conditional transition loss

The revenue and operational cost transmission channels are interconnected. Since carbon costs are proportional to a firm's carbon intensity, total operating costs depend on activity levels, which are in turn determined by firm revenue. To better understand the relative contribution of each transmission channel, this relationship is further analysed. Specifically, we calculate the sensitivity of DCF to changes in carbon cost rate $\omega_{i,t}$ and projected sales $Y_{i,t}$:

$$\frac{\partial DCF_{i,t}}{\partial \omega_{i,t}} = -\frac{Y_{i,t}}{\left(1+WACC\right)^t}$$

$$\frac{\partial DCF_{i,t}}{\partial Y_{i,t}} = -\frac{\left(1-\omega_{i,t}-\tau-\theta-\rho\right)}{\left(1+WACC\right)^t}$$

These partial derivatives give us the sensitivity of the discounted cashflows to the carbon costs rate and sales:

$$\frac{\partial^2 DCF_{i,t}}{\partial \omega_{i,t}\partial Y_{i,t}} = -\frac{1}{\left(1+WACC\right)^t}$$

The impact on the discounted cashflows of the stock i due to the climate scenarios can thus be described as:

$$\Delta DCF_{i,t}^{Y} = \frac{\partial DCF_{i,t}}{\partial Y_{i,t}} \times \Delta Y_{i,t}$$

$$\Delta DCF_{i,t}^{\omega} = \frac{\partial DCF_{i,t}}{\partial \omega_{i,t}} \times \Delta \omega_{i,t}$$

$$\Delta DCF^{Y\times\omega} = \frac{\partial^2 DCF_{i,t}}{\partial \omega_{i,t}\partial Y_{i,t}} \times \Delta\omega_{i,t}\Delta Y_{i,t}$$

where $\Delta Y_{i,t}$ and $\Delta\omega_{i,t}$ are the differences in the projected sales and the carbon costs rate between the initial expected transition scenario and the new market expectations. The total impact of the transition scenario on firm i's discounted cash flows can thus be expressed as:

$$\Delta DCF_{i,t} = \Delta DCF_{i,t}^{Y} + \Delta DCF_{i,t}^{\omega} + \Delta DCF_{i,t}^{Y\times\omega}$$

The change in stock value due to unexpected transition concerns is:

$$\Delta V_i = \Delta V_t^{Y} + \Delta V_t^{\omega} + \Delta V_t^{Y\times\omega}$$

The loss from each factor is computed as a ratio to the baseline stock value:

$$L_i^{Y} = -\left(\frac{\Delta V_i^{Y}}{V_i^{baseline}}\right)$$

$$L_i^{\omega} = -\left(\frac{\Delta V_i^{\omega}}{V_i^{baseline}}\right)$$

$$L_i^{Y\times\omega} = -\left(\frac{\Delta V_i^{Y\times\omega}}{V_i^{baseline}}\right)$$

where $V_i^{baseline}$ is the value of the stock in the initially expected transition scenario. The loss from net carbon tax is computed as the loss from carbon netted from the interaction term:

$$L_i^{\omega^{net}} = L_i^{\omega} + L_i^{Y\times\omega}$$

2 Every rate is expressed as a fraction of the sales. It allows us to factorise the sales in the cashflows formula.

The total loss of the stock can therefore be expressed as:

$$L_i = L_i^Y + L_i^{\omega^{net}}$$

This decomposition captures the repricing effects of unexpected change in transition concerns through two main dimensions: the net carbon tax effect and the revenue effect.

Model calibration
The growth factors – specific to each activity segment – and the carbon price are calibrated based on the NGFS scenarios database.[3]

The Current Policies scenario serves as the reference, while Net Zero 2050 is the primary 'adverse' transition scenario. Certain segments, particularly climate policy-relevant sectors (Battiston et al [2017]), face heightened transition risks. For these, relevant NGFS scenario variables serve as proxies to estimate revenue growth factors (figure 1). The growth factor is defined as $Y_{s,t}/Y_{s,0}$, where $Y_{s,t}$ is the demand of the product s at time t and $Y_{s,0}$ is the demand of the product s at the base year (2020).

The initial revenue for each activity segment, $Y_{i,s,0}$, is determined using the European Sustainable Taxonomy (Moody's Product & Services dataset) in conjunction with the NACE classification.[4] The weighted average cost of capital (WACC), tax rate (τ), operating costs rate (θ) and net investments rate (ρ) are calibrated with the global version of the Damodaran Online database[5] at TRBC sector level[6] (figure 2).

1. Activity segments and scenario variables

Activity segment	NGFS variable used to calibrate the growth factor
Other	GDP|MER|Counterfactual without damage
Fossil Fuels Electricity	Secondary Energy|Electricity|Coal
	Secondary Energy|Electricity|Gas
	Secondary Energy|Electricity|Oil
Low Carbon Electricity	Secondary Energy|Electricity|Biomass
	Secondary Energy|Electricity|Geothermal
	Secondary Energy|Electricity|Hydro
	Secondary Energy|Electricity|Solar
	Secondary Energy|Electricity|Wind
	Secondary Energy|Electricity|Nuclear
Fossil Fuels	Primary Energy|Coal
	Primary Energy|Gas
	Primary Energy|Oil
	Secondary Energy|Gases
	Secondary Energy|Liquids
Hydrogen	Secondary Energy|Hydrogen
Alternative Transportation	Final Energy|Transportation|Electricity
	Final Energy|Transportation|Hydrogen
Conventional Transportation	Final Energy|Transportation|Liquids

Note: This table presents mapping between specific segment activities and corresponding NGFS scenario variables used to proxy revenue trend of each segment.

2. Calibration parameters by TRBC sector

Sector	WACC	τ	θ	ρ
Industrials	0.091	0.201	0.116	0.071
Basic materials	0.094	0.140	0.090	0.038
Cyclical consumer	0.091	0.138	0.308	-0.005
Energy	0.086	0.136	0.068	0.022
Financials	0.075	0.036	0.232	-0.032
Non-cyclical consumer	0.073	0.174	0.241	0.122
Technology	0.107	0.079	0.270	0.026
Telecoms	0.077	0.178	0.309	0.016
Utilities	0.082	0.141	0.190	0.116
Total	0.064	0.125	0.221	0.032

Note: This table presents calibrated parameters for different TRBC sectors, including weighted average cost of capital (WACC), tax rate (τ), operating costs rate (θ), and net investments rate (ρ). The WACC is calibrated using the field cost of capital. The tax rate (τ) is derived from the tax rate field. The operating costs rate (θ) is calculated by subtracting the pre-tax, pre-stock compensation operating margin from the gross margin. The net investments rate (ρ) is calibrated using the field net capex/sales.

Results

Applying the model to the 1,287 largest listed companies worldwide[7] reveals that the revenue transmission channel has a comparable impact to carbon pricing. Incorporating both channels reveals heterogeneous impacts within transition-sensitive sectors, offering additional insights beyond carbon intensity as a risk proxy. Lastly, the analysis examines the sensitivity of these findings to scenario and time horizon choices.

The revenue transmission channel as a key driver
Unlike short-term assessments of carbon pricing on operating costs, this long-term scenario analysis accounts for demand shifts across activity segments. The revenue transmission channel has a greater aggregate impact than carbon pricing across most sectors, including low-emission industries (healthcare, telecoms, technology) influenced by GDP trends and transition-sensitive sectors (utilities, energy, industrials) where 'green' segments grow as 'brown' segments decline. Overall, utilities, energy, basic materials[8] and industrials suffer the greatest losses, with utilities facing a potential value loss of up to 58% (figure 3).

3 Scenarios are based on three Integrated Assessment Models (IAMs): GCAM 6.0 NGFS, MESSAGEix-GLOBIOM 1.1-M-R12 and REMIND-MAgPIE 3.2-4.6. We focus on MESSAGEix-GLOBIOM 1.1-M-R12 model for results presentation.
4 For each stock, revenue is allocated as follows: a) percentages from Moody's dataset are assigned to activity segments; (b) The remainder is allocated by NACE code, with unmapped activities 'Other'.
5 https://pages.stern.nyu.edu/~adamodar/New_Home_Page/data.html
6 Stocks without a TRBC sector are assigned to the total sector, calibrated with the total market. Due to lack of data, we assign stocks from the healthcare sector to the total sector.
7 Constituents of the MSCI World Index.
8 Basic materials displays a revenue-to-carbon-tax ratio of only 0.05, making it almost immune to the revenue dimension. Its high exposure to carbon taxes likely stems from minimal expected demand shifts under transition scenarios. Decarbonisation in this sector depends more on energy supply chain shifts (energy and utilities) than on demand-side changes.

3. Conditional transition loss per sector

Sector	Total (%)	From net carbon tax (%)	From revenue (%)	Revenue impact/carbon tax impact ratio
Utilities	57.9	22.2	35.6	**1.6**
Energy	33.1	12.4	20.7	**1.7**
Basic materials	22.0	20.1	1.0	0.1
Industrials	9.8	4.9	5.0	**1.0**
Non-cyclical consumer	4.7	3.0	1.8	0.6
Financials	3.1	1.2	1.9	**1.5**
Healthcare	2.5	0.7	1.7	**2.5**
Telecoms	2.1	0.3	1.8	**6.3**
Technology	1.8	0.3	1.5	**4.6**
Cyclical consumer	-1.6	1.7	-3.3	**1.9**
MSCI World	**5.9**	**2.9**	**3.0**	**1.0**

Note: The table presents the weighted average conditional transition loss for each sector, decomposed into total loss, net carbon tax loss, and revenue loss under the Net Zero 2050 scenario (MESSAGEix-GLOBIOM 1.1-M-R12 model). The revenue impact/carbon tax impact ratio compares revenue-driven losses to carbon tax losses. Ratios above 1 (in bold) indicate revenue shifts outweigh carbon tax effects, while those below 1 suggest the opposite. Negative total loss values reflect net gains.

4. Summary statistics by sector

Sector	No of stocks	Mean	Std dev	Min	Max	Q1	50%	Q3
a) Conditional transition loss (total, %)								
Utilities	69	51.8	27.3	-97.5	71.1	49.5	58.9	67.3
Energy	59	30.8	22.1	-84.6	57.1	27.4	33.3	43.8
Basic materials	88	22.0	20.2	-0.7	66.7	5.1	15.2	33.0
Industrials	215	8.4	13.1	-13.7	65.1	1.9	2.5	7.8
MSCI World	**1,287**	**9.2**	**17.0**	**-97.5**	**71.1**	**1.8**	**2.2**	**5.3**
b) Loss from net carbon tax (%)								
Utilities	69	22.4	25.4	0.0	138.0	5.1	16.9	30.2
Energy	59	12.7	10.3	0.1	33.9	4.9	9.5	18.4
Basic materials	88	20.3	20.3	0.1	64.3	4.0	13.6	32.0
Industrials	215	4.2	10.6	0.0	63.4	0.3	0.7	1.5
MSCI World	**1,287**	**4.7**	**11.7**	**0.0**	**138.0**	**0.1**	**0.4**	**2.3**
c) Loss from revenue (%)								
Utilities	69	29.3	31.9	-97.9	49.0	20.2	46.5	48.9
Energy	59	18.0	16.1	-85.0	340.0	23.2	23.3	23.3
Basic materials	88	1.6	3.1	-17.4	21.9	1.6	1.6	1.6
Industrials	215	4.2	6.5	-15.2	18.4	1.7	1.7	1.7
MSCI World	**1,287**	**4.6**	**11.3**	**-97.9**	**49.0**	**1.7**	**1.7**	**1.8**

Note: Summary statistics for total loss, loss from net carbon tax, and loss from revenue are presented for utilities, energy, basic materials, industrials and the MSCI World index under the Net Zero 2050 scenario using the MESSAGEix-GLOBIOM 1.1-M-R12 model. The data includes mean, standard deviation, minimum, maximum, and quartiles (Q1, median, Q3) for each sector. Total loss reflects overall transition risk impacts, while net carbon tax and revenue losses isolate carbon pricing and revenue effects. Negative values indicate gains.

Heterogeneous impact for firms within the climate sensitive sectors

Transition risk scenario analyses using integrated assessment models provide sector-level financial impact assessments. However, portfolio managers must understand both the sectoral and intra-sectoral dimensions of transition risks. Incorporating the revenue transmission channel alongside carbon pricing reveals significant heterogeneity. Unlike stress tests focused solely on carbon pricing, this approach highlights potential positive revaluations, particularly in energy and utilities, where both 'winners' (stocks with negative losses) and 'losers' emerge (figure 4).

A limited overlap between the carbon intensity and the conditional transition loss

Carbon intensity, defined as emissions relative to revenue or enterprise value, is often used as a proxy for transition risks in equity markets. While related to conditional transition loss, this analysis reveals significant divergence due to the influence of revenue, especially in utilities (figure 5).

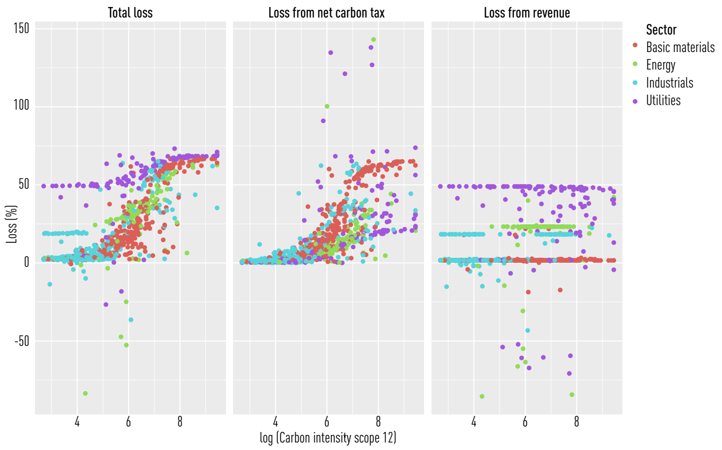
Sensitivity analysis to scenario, model, and horizon

Long-term scenario analysis differs from traditional risk management by extending the horizon to as far as 2050 and incorporating multiple scenarios without assigned probabilities. Consequentially, assessing sensitivity to these parameters is crucial.

All transition scenarios result in significantly lower conditional transition losses than the Net Zero 2050 scenario (figure 6). Aggregate losses range from 0.4% under the Fragmented World scenario to 6.2% under Net Zero 2050, illustrating the potential range of transition risk impacts.

Time horizon plays a significant role,

5. Relationship between carbon intensity and conditional transition loss



Note: The graphics display the relation between carbon intensity and various loss types across utilities, energy, basic materials and industrials under the Net Zero 2050 scenario (MESSAGEix-GLOBIOM 1.1-M-R12). Each plot presents loss sensitivity to carbon intensity levels, measured as the logarithm of Scope 1 + 2 intensities. The subplots illustrate the total loss, loss from net carbon tax, and loss from revenue. Winsorisation at the 1st and 99th percentiles mitigates extreme values. Log transformation allows for a more balanced visualisation.

with the conditional transition loss with the conditional transition loss increasing from 2.5% at a 2030 horizon to 6.2% by 2050. Despite discounting reducing long-term cash flow impacts, most transition risks emerge after 2030 (figure 7).

The balance between the revenue mechanism and the carbon price transmission channel shifts with the time horizon. By 2030, losses are largely driven by the carbon tax, but beyond 2030, revenue dynamics become the primary driver (figure 8). Our results exhibit limited sensitivity to the choice of the integrated assessment model. For the aggregate universe, the maximum variation in conditional transition loss across models is 1.2% (ranging from 6.2% to 5.1% – figure 9).

Combining the sensitivities to each parameter indicates that conditional transition loss is predominantly influenced by scenario and time horizon choices. Model uncertainties have a smaller impact (figure 10).

Discussion and conclusion

This study enhances the understanding of climate transition risks by integrating firm-level data into long-term scenario analysis to quantify financial impacts in equity portfolios. By incorporating revenue (demand shifts) and operational cost transmission (carbon pricing), it reveals significant intra-sectoral variation. Utilities and other climate-related sectors show mixed effects, with some firms benefiting and others incurring losses. These findings highlight the limitations of carbon intensity as a proxy for transition risks.

Long-term forward-looking scenario analyses are challenging to compare due to varying assumptions. Our findings, slightly lower than existing studies (figure 11), reflect the inclusion of transition benefits, unlike most studies that focus solely on losses. For energy and utilities –the most sensitive sectors – our results rank in the upper half for transition losses (figure 12). While estimates of conditional transition loss vary widely, sector-specific ranges emerge: diversified portfolios face losses of 0-15%, while sector-specific losses are broader – 10-50% for energy and 10-80% for utilities – highlighting substantial sectoral heterogeneity in transition risks.

The sensitivity analysis underscores the substantial impact of scenario design and time horizon on transition risk. Despite discounting effects, most conditional transition loss arises from cash flows beyond 2030, emphasising the need for forward-looking approaches. Practitioners and regulators should adopt integrated methodologies that capture

6. Conditional transition loss sensitivity to scenario

Sector	Net Zero 2050	Below 2°C	Delayed transition	Fragmented world	Max-Min
Utilities	57.9	26.6	21.7	9.9	47.9
Energy	33.1	9.8	7.5	3.3	29.8
Basic materials	22.0	2.9	2.7	1.1	20.9
Industrials	9.8	2.6	2.0	1.2	8.6
MSCI World	**6.2**	**1.2**	**1.0**	**0.4**	**5.8**

Note: This table displays sectoral losses across transition scenarios – Net Zero 2050, Below 2°C, Delayed transition and Fragmented world. The Max-Min column captures the difference between maximum and minimum losses, indicating each sector's sensitivity to transition risks. Higher values denote greater sensitivity; lower values suggest stability across scenarios.

7. Conditional transition loss sensitivity to horizon

Sector	2030	2050	2030/2050	Max-Min
Utilities	29.3	57.9	0.5	28.5
Energy	12.5	33.1	0.4	20.6
Basic materials	9.0	22.0	0.4	13.0
Industrials	3.1	9.8	0.3	6.8
MSCI World	**2.5**	**6.2**	**0.4**	**3.7**

Note: This table presents sectoral loss sensitivity to time horizons (2030 vs 2050), with percentage losses for each sector at both points. The 2030/2050 column reflects near-term versus long-term impacts, while the Max-Min column captures the range of change over time. Higher Max-Min values indicate greater variation; lower values suggest more stability.

8. Revenue impact/carbon impact ratio

Sector	2030	2050
Utilities	0.7	1.6
Energy	0.9	1.7
Basic materials	0.1	0.1
Industrials	0.6	1.0
MSCI World	**0.7**	**1.0**

Note: This table displays the ratio of revenue impact to carbon tax impact across sectors for 2030 and 2050. A ratio above 1 indicates revenue impact exceeds carbon tax impact, while a ratio below 1 suggests the opposite. Shifts between 2030 and 2050 highlight how the relative importance of these factors evolves over time.

9. Conditional transition loss sensitivity to model

Sector	MESSAGEix-GLOBIOM 1.1-M-R12	GCAM 6.0 NGFS	REMIND-MAgPIE 3.2-4.6	Max-Min
Utilities	57.8	51.1	56.5	6.7
Energy	33.1	22.7	26.3	10.4
Basic materials	22.0	12.2	13.2	9.8
Industrials	9.8	5.9	5.0	4.8
MSCI World	**6.2**	**5.2**	**5.1**	**1.2**

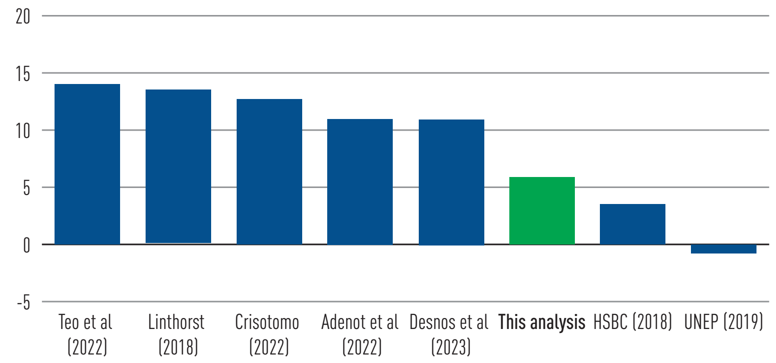
Note: This table shows sectoral loss sensitivity to different climate economy models – MESSAGEix-GLOBIOM 1.1-M-R12, GCAM 6.0 NGFS and REMIND-MAgPIE 3.2-4.6 – under the Net Zero 2050 scenario. The Max-Min column captures the range of variability in model outcomes.

10. Conditional transition loss sensitivity to the main parameters

Sector	Max-Min scenario	Max-Min horizon	Max-Min model
Utilities	47.9	28.5	6.7
Energy	29.8	20.6	10.4
Basic materials	20.9	13.0	9.8
Industrials	8.6	6.8	4.8
MSCI World	**5.8**	**3.7**	**1.2**

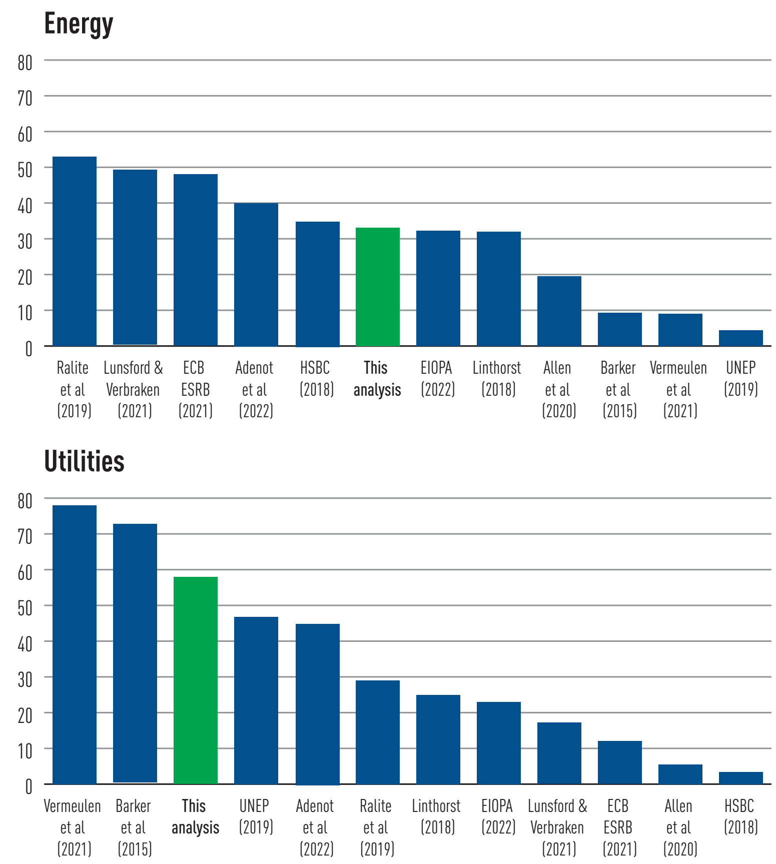
Note: This table presents sectoral loss sensitivity to calibration settings, including scenario (Max-Min scenario), time horizon (Max-Min horizon) and integrated assessment model (Max-Min model). The values indicate the range of potential outcomes by measuring the difference between maximum and minimum losses.

11. Comparison of conditional transition loss estimates in the literature for a diversified equity portfolio



Note: The exhibit displays the conditional transition loss per sector for a diversified portfolio, using each study's most stringent scenario. The selected horizon corresponds to either the study's default or the one yielding the most adverse outcomes.

12. Comparison of conditional transition loss estimates in the literature for transition-sensitive sectors



Note: The exhibit displays total sectoral losses for a diversified portfolio under each study's most stringent scenario. Horizons align with default settings or the most adverse outcomes. Sector classifications were standardised to TRBC sectors (energy and utilities), with median values used where aggregation was needed.

revenue and operational cost impacts while leveraging complementary scenarios and models.

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Attribution analysis of equity portfolio emissions: examining and integrating existing frameworks

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Understanding the drivers influencing greenhouse gas emissions in financial portfolios is crucial for constructing and monitoring climate investment strategies. Several attribution frameworks have recently emerged to identify the drivers of portfolio decarbonisation. This article (a summary of a recent research paper[1]) compares existing frameworks, exploring key drivers and methods to isolate their effects. Building on this review, a flexible three-step model is formalised to integrate these drivers, and five specific models are developed to address climate-related questions. These models should help investors to better understand portfolio emissions changes and distinguish external factors from those they can directly influence.

Key takeaways

Since 2022, several attribution frameworks have emerged to help investors understand changes in emissions metrics – absolute emissions, intensity and footprint – in financial portfolios.

These frameworks classify the drivers into four main categories: data coverage, portfolio reallocation, economic and financial fluctuations, and company emissions. Two common attribution methods are Laspeyres indicators and the logarithmic mean Divisia index.

The drivers are complementary and can be integrated into a flexible three-step model to assess contributions from strategic asset allocation, divestment, sector shifts, stock selection, price volatility, emissions scopes, company activity and inflation.

Introduction

Asset owners can help mitigate climate change by reducing portfolio emissions. Regulatory and voluntary frameworks that define metrics, harmonise reporting standards, and align reduction targets with the Paris Agreement[2] support these efforts. However, despite progress, investors still face challenges in controlling portfolio emissions.

Since 2022, attribution frameworks have emerged to clarify emissions drivers (Bouchet [2023], NZAOA [2023], Nagy, Giese and Wang [2023], Simmons et al [2022]). NZAOA (2023) highlights attribution analysis as a tool for investors to take informed action via divestment, reallocation, engagement or challenging asset managers. It also improves transparency in public reporting, aligning with Science Based Targets initiative (SBTi) recommendations.

This article compares key attribution frameworks and explores how combining them can provide greater flexibility for investors.

The first section analyses attribution frameworks by portfolio type, emissions metric, key drivers and attribution method. Most assess absolute emissions, emissions intensity and footprint, with changes driven by data coverage, portfolio reallocation, economic shifts and company emissions. Differences arise mainly in reallocation, with some models emphasising investment universe changes and others sectoral shifts.

Emissions changes are attributed using either Laspeyres price and quantity indicators (commonly used in price index analysis) or the logarithmic mean Divisia index (LMDI), an environmental economics approach better suited for models with multiple drivers.

1 Bouchet, V. (2025). *Attribution Analysis of Equity Portfolio Emissions: Examining and Integrating Existing Frameworks.* Scientific Portfolio Publication.

2 EU climate transition and Paris-aligned benchmarks delegated regulation, target setting protocol of the Net-Zero Asset Owner Alliance, net-zero investment framework of the Paris Aligned Investment Initiative.

The comparative analysis finds that different frameworks offer complementary insights. To enhance adaptability, a flexible three-step model integrates these drivers. Applied to a fictitious four-company portfolio, it examines five climate-related questions, assessing asset allocation, divestment, stock selection, market volatility, emissions scopes, company activity and inflation.

Attribution analysis helps investors distinguish between external factors (eg, price volatility) and those they can influence (eg, divestment, sector allocation, stock selection). This makes it a key tool for building and monitoring climate investment strategies. The generalised model proposed enhances flexibility and implementation, adapting to investors' needs.

Review of existing attribution frameworks

This section compares attribution frameworks by Simmons et al (2022), Bouchet (2023), Nagy, Giese and Wang (2023) and NZAOA (2023). These frameworks vary in portfolio types, emissions metrics, identified drivers and methods used to attribute changes in emissions.

Portfolios, metrics and type of analysis

The portfolio's asset class determines the appropriate emissions metrics, varying by instrument type: listed, debt, equity, company, project, real estate or sovereign. Attribution frameworks primarily focus on equity portfolios, particularly benchmarks or indices (figure 1).

Existing attribution frameworks analyse three complementary emissions metrics: absolute emissions, emissions intensity and emissions footprint. These cover Scope 1 (direct emissions), Scope 2 (indirect emissions from energy use) and Scope 3 (indirect value chain emissions). Scope 3 inclusion remains debated due to scale and methodological challenges (Ducoulombier [2021, 2024]). The second section explores how attribution analysis disentangles the contributions of each scope.

Most attribution frameworks analyse portfolios over time, crucial for assessing contributions to emissions reduction targets. Cross-sectional analysis can supplement this by comparing two portfolios at a given moment.

Drivers that explain change in an emissions metric

The drivers in existing frameworks vary depending on whether the metric is absolute emissions or intensity-based, but they generally fall into four categories (figure 2). The first relates to *data coverage*, where emissions may change due to variations in data availability. Methodological changes, especially for Scope 3, also fall into this category.

The second category, *portfolio reallocation*, includes buy and sell decisions affecting portfolio composition. These shifts are captured through changes in instrument weight – driven by transactions and financial fluctuations – and the portfolio's share of a company, which only changes through transactions. Bouchet (2023) further differentiates between sector allocation and stock selection drivers.

The third category concerns *economic and financial fluctuations*. Variations in enterprise value, including cash (EVIC), particularly in the equity component,

1. Review of existing portfolios, metrics and types of analysis

Framework	Portfolio analysed	Metrics	Type of analysis
Simmons et al (2022)	Equity benchmark (FTSE All-World Index)	Emissions intensity	Historical
Bouchet (2023)	Equity index (climate impact index)	Absolute emissions	Cross-sectional
		Emissions intensity	Historical
Nagy, Giese and Wang (2023)	Equity benchmark (MSCI ACWI Investable Market Index)	Absolute emissions	Historical
		Emissions intensity	
	Exchange-traded fund (US minimum volatility ETF)	Emissions footprint	
NZAOA (2023)	(Listed) corporate bonds and equity portfolio	Absolute emissions	Historical
		Emissions intensity	
		Emissions footprint	

2. Drivers in existing attribution frameworks

Driver type	Driver	Bouchet (2023)	Nagy, Giese and Wang (2023)	NZAOA (2023)
a) Analysis of change in absolute emissions				
Data coverage	Data coverage		X	X
Portfolio reallocation (buy/selldecisions)	New positions		X	X
	Deleted positions		X	X
	Financing share		X	
Portfolio reallocation (buy/selldecisions) *and/or* financial fluctuations	Sector weight	X		
	Instrument weight within sector	X		
	Financing value			X
	Portfolio AUM	X		
Financial and economic fluctuations	Financing structure		X	
	EVIC	X		X
	Revenue	X		
Financial and economic fluctuations *and/or* company emissions	Emissions intensity	X		
Company emissions	Emissions		X	X

Driver type	Driver	Simmons et al (2022)	Bouchet (2023)	Nagy, Giese and Wang (2023)	NZAOA (2023)
b) Analysis of change in emissions intensity or footprint					
Data coverage	Data coverage			X	X
Portfolio reallocation (buy/selldecisions)	New positions	X		X	X
	Deleted positions	X		X	X
Portfolio reallocation (buy/selldecisions) *and/or* financial fluctuations	Sector weight		X		
	Instrument weight within sector		X		
	Instrument weight within portfolio	X		X	X
Financial and economic fluctuations	Revenue	X		X	X
Financial and economic fluctuations *and/or* company emissions	Emissions intensity		X		
Company emissions	Emissions	X		X	X

Note: Various frameworks use different terms for key drivers.

affect financial structure (equity versus debt) and portfolio emissions. Since these factors are largely external to investors, isolating their effects is key to identifying investor-driven emission reductions.

The final category relates to *company emissions*, which fluctuate due to changes in emissions intensity or revenue. However, revenue changes may not accurately reflect production efficiency gains, warranting the inclusion of an inflation driver.

Methods of attribution

Two main methods are used to attribute changes in emissions metrics to driver: the Laspeyres and LMDI methods. Let M_p represent an emission metric at portfolio level which can be expressed as the sum for J instruments of a product of N variables (drivers):

$$M_p = \sum_{j=1}^{J} M_j = \sum_{j=1}^{J} D_{1,j}.D_{n,j}\ldots.D_{N,j} = \sum_{j=1}^{J}\prod_{n=1}^{N} D_{n,j}$$

where M_j represents the contribution of instrument j to the portfolio metric, and $D_{n,j}$ represents the contribution of driver n to M_j.

The goal of an attribution method is to express the change from M_p^{t0} to M_p^{t1} as an additive[3] decomposition of effects E_{D_n} corresponding to each driver D^n.

$$M_p^{t1} - M_p^{t0} = \Delta M_p = E_{D_1} + E_{D_n} + \cdots + E_{D_N}$$

Nagy, Giese and Wang (2023) and NZAOA (2023) use a method based on Laspeyres (1871) price and quantity indicators, commonly used to analyse changes in price indexes. This method is analogous to decomposition framework for a portfolio's financial performance (Brinson and Fachler [1985], Brinson, Hood and Beebower [1986]). The case of two drivers illustrates this method:

$$M_p = \sum_{j=1}^{J} D_{1,j}.D_{2,j}$$

$$\Delta M_p = \underbrace{\sum_{j=1}^{J}\Delta D_{1,j}.D_{2,j,t0}}_{E_{D_1}} + \underbrace{\sum_{j=1}^{J}\Delta D_{2,j}.D_{1,j,t0}}_{E_{D_2}} + \underbrace{\sum_{j=1}^{J}\Delta D_{1,j}.D_{2,j}}_{I_{\Delta D_1,\Delta D_2}}$$

where $I_{\Delta D_1,\Delta D_2}$ is an interaction term between the two variations ΔD_1 and ΔD_2. One limitation of this method is the difficulty in interpreting the interaction terms. Simmons et al (2022) and Bouchet (2023) rely on Divisia index, commonly used environmental economics (Ang, Zhang and Choi [1998]). As developed in Ang (2015), the additional effects of the driver D_n is given by:

$$E_{D_n} = \sum_{j=1}^{J} L\left(M_j^{t1}, M_j^{t0}\right).\ln\left(\frac{D_{n,j,t1}}{D_{n,j,t0}}\right)$$

where

$$L\left(M_j^{t1}, M_j^{t0}\right) = M_j^{t1} - M_j^{t0} / \ln\left(M_j^{t1}\right) - \ln\left(M_j^{t0}\right)$$

Driver effects using Laspeyres are easier to interpret by isolating their impact while holding others constant. But it lacks symmetry – analysing $t0$ to $t1$ versus $t1$ to $t0$ yields different results. As more drivers are considered, interaction terms increase. These can be eliminated using the average method, but the results remain sensitive to the order of decomposition. For example, decomposing $M_j = D1.D2.D3$ differs from $M_j = D3.D2.D1$.

LMDI eliminates interaction terms, is symmetrical, and is not sensitive driver order, though the effects calculated using LMDI are more complex to interpret due to logarithms, and handling zero values requires attention.

Laspeyres is recommended for models with two drivers, while LMDI is preferable for models with more.

Model and data

Attribution frameworks provide complementary insights into portfolio emissions by analysing different drivers. This section introduces a flexible model integrating these drivers, using a fictitious portfolio as its basis.

A flexible model to combine drivers

The model consists of three steps.

Step 1: Defining groups of financial instruments with the portfolio

Let $\mathcal{P}$ represent the set of all portfolio instruments. The first step defines disjoint subsets $\mathcal{P}_k$ within $\mathcal{P}$ to isolate contributions as drivers (eg, divested instruments or sector-specific groups).

$$\mathcal{P} = \bigcup_{k=1}^{K} \mathcal{P}_k$$

with $\mathcal{P}_k \cup \mathcal{P}_l = \varnothing$ for all $k \neq l$, and K is the number of subsets.

Step 2: Choosing drivers

The second step defines a set of N_k drivers whose product equals the instrument contribution to the emissions metric[4] $M_{p,t}$.

$$M_{p,t} = \sum_{k=1}^{K} f_k\left(\sum_{j\in\mathcal{P}_k} D1_j.Dn_j.\ldots.DN_{kj}.\right)$$

These factors can differ depending on the subset. In the case of absolute emissions, we might be only interested by the absolute emissions associated with an instrument for the subset 'divested assets' but by more drivers for the other instruments.

$$M_{p,t} = \sum_{j\in\mathcal{P}\,Divested\ instruments} M_j^p + \sum_{j\in\mathcal{P}\,Remaining\ instruments} \underbrace{D1_j.D2_j\ldots DN_{kj}}_{E_j^P}$$

Step 3: Choosing an attribution method

The third step is to choose an attribution method, to determine the effect of any driver D_n, between the Laspeyres method (with and without interaction terms) and the LMDI method (figure 3).

Fictitious portfolio and companies

A portfolio of four financial instruments, covering equity and debt from four fictitious companies, is analysed over one period ($t0$ to $t1$). Two companies belong to a carbon-intensive ('brown') sector (BS) and two to a low-carbon ('green') sector (GS), with one high-intensity (HI) and one low-intensity (LI) firm in each. Figures 4 and 5 detail changes in company variables and portfolio reallocation. Over

3. Effect calculation for three attribution methods

Method	Formula for E_{D_n}
Laspeyres with interaction terms	$E_{D_n} = \Delta D_n.\prod_{k\neq n} D_{k,t0}$
Laspeyres without interaction terms	$E_{D_n} = \Delta D_n.\overline{\prod_{k=n+1}^{N}} D_k.\prod_{k=1}^{n-1}\overline{D_k}$
Logarithm mean Divisia index (LDMI)	$E_{D_n} = \sum_{j=1}^{J}\left[\left(\frac{M_j^{t1} - M_j^{t0}}{\ln\left(M_j^{t1}\right) - \ln\left(M_j^{t0}\right)}\right).\ln\left(\frac{D_{n,j,t1}}{D_{n,j,t0}}\right)\right]$

Note: As discussed earlier, for D_n, (the financial weight driver), the initial portfolio emissions metric (intensity or footprint) can be subtracted, regardless of the method used.

3 While it is less common in the existing attribution frameworks, the attribution can also be multiplicative. In this case, the change in the emissions metric is expressed as follows: $M^{t1}/M^{t0} = E_{D_1}.E_{x_2}.....E_{D_n}$.

4 Absolute emissions, emissions intensity or emissions footprint.

4. Changes in company variables

Company (i)	Sector	Unit	BS-HI $i \in S_{brown}$	BS-LI $i \in S_{brown}$	GS-HI $i \in S_{green}$	GS-LI $i \in S_{green}$
Emissions and economic activity	$E1_{i,t0}$	(tCO_2e)	75,000,000	25,000,000	15,000,000	5,000,000
	$E1_{i,t1}$	(tCO_2e)	-	50,000,000 **(a)**	-	-
	$E2_{i,t0}$	(tCO_2e)	25,000,000	12,500,000	5,000,000	2,500,000
	$E2_{i,t1}$	(tCO_2e)	12,500,000 **(b)**	6,250,000 **(b)**	2,500,000 **(b)**	1,250,000 **(b)**
	$P_{i,t0}$	t	100	100	100	100
	$P_{i,t1}$	t	-	-	-	-
	$R_{i,t0}$	($m)	100,000	100,000	100,000	100,000
	$R_{i,t1}$	($m)	-	150,000 **(c)**	-	-
Financing structure	$QE1_{i,t0}$		100,000,000	100,000,000	100,000,000	100,000,000
	$QE1_{i,t1}$		-	-	-	-
	$PE2_{i,t0}$	($)	1,000	1,000	1,000	1,000
	$PE2_{i,t1}$	($)	1,200 **(d)**	1,300 **(d)**	1,300 **(d)**	1,500 **(d)**
	$QD1_{i,t0}$	-	50,000,000	50,000,000	50,000,000	50,000,000
	$QD1_{i,t1}$	-	-	-	-	100,000,000
	$PD_{i,t0}$	-	1,000	1,000	1,000	1,000
	$PD_{i,t1}$	-	-	-	-	-
	$EVIC_{i,t0}$	($m)	150,000	150,000	150,000	150,000
	$EVIC_{i,t1}$	($m)	170,000	180,000	180,000	250,000 **(e)**

Notation: E1 = direction emissions (Scope 1), E2 =direct emissions from electricity (Scope 2), P = physical production (tonnes), R = revenue, QE = quantity of equity instruments, PE = equity price, QD = debt quantity, PD = debt price, EVIC = enterprise value including cash. Scenario: BS-LI's direct emissions double (100%) (a) while revenue rises 50% (c). Indirect emissions from electricity fall 50% (b). Equity prices increase 20–50% (d), raising EVIC. GS-LI's EVIC also rises due to debt issuance (e).

the period, absolute emissions decrease from 19,677 tCO_2e to 14,945 tCO_2e, while emissions intensity decreases from 295.0 tCO_2e/$m to 181.2 tCO_2e/$m.

Results

This section refines the flexible model to address key questions related to three of the four driver categories (figure 6). Since these models often require more than three drivers, the LMDI method is used for attribution, though the other methods remain applicable.

Effects of asset class and sector allocation on portfolio absolute emissions

To assess the impact of asset class (equity versus debt) and sector[5] (brown versus green), on absolute emissions changes, an initial model applies only the first step – defining disjoint portfolio subsets. This analysis reveals that most reductions in the fictitious portfolio stem from equity divestments in the brown sector (figure 7 7).

Effects of divestment and reallocation on absolute emissions

It is essential to determine whether the reduction stems from divestment, reallocations within the brown sector, or reductions in emissions.

A second model assesses divestment impacts and the effects of purchases or sales, financial fluctuations (price volatility and financial structure), and emissions of remaining instruments.

5 We use a simplified binary classification here, though climate-specific classifications can be applied.

5. Changes in a multi-asset portfolio

Instrument	Unit	BS-HI	BS-LI	GS-HI	GS-LI
Type of instrument		**Equity**	**Equity**	**Debt**	**Debt**
N_{j0}		10,000	30,000	30,000	30,000
N_{j1}		0.0	19,384	63,000	25,200
$PI_{j,t0}$	$	1,000	1,000	1,000	1,000
$PI_{j,t1}$	$	1,200	1,300	-	1,500
$w_{j,0}$	%	10.0	30.0	30.0	30.0
$w_{j,1}$	%	0.0	20.0	50.0	30.0
$w_{s(i(j)),t0}$	%	40.0	40.0	60.0	60.0
$w_{s(i(j)),t1}$	%	20.0	20.0	80.0	80.0
$w_{is(i(j)),t0}$	%	25.0	75.0	50.0	50.0
$w_{is(i(j)),t1}$	%	0.0	100.0	62.5	37.5

Notation: N = instrument quantity, PI = price per instrument, w = financial weight in portfolio, w_s = sector weight, w_{is} = instrument's financial weight in sector (w_{is}=w/w_s). Scenario: The portfolio manager fully divests from BS-HI, reduces BS-LI exposure, and reallocates to GS-HI debt instruments.

6. Climate-related questions and specific model associated

Question	Specific model
What is the contribution of each asset class and each climate-sensitive sector?	$E_p = \sum_{j \in \mathcal{P}Equity\,\&\,brown} E_j^p + \sum_{j \in \mathcal{P}Equity\,\&\,green} E_j^p + \sum_{j \in \mathcal{P}Debt\,\&\,brown} E_j^p + \sum_{j \in \mathcal{P}Debt\,\&\,green} E_j^p$
What is the contribution of divestment and reallocation in this reduction?	$E_p = \sum_{j \in \mathcal{P}Divested\ instruments} E_j^p + \sum_{j \in \mathcal{P}Remaining\ instruments} \underbrace{N_j}_{buy/sell} \underbrace{PI_j . \frac{1}{EVIC_{i(j)}}}_{Financial\ fluctuations} .E_{i(j)}$ $EI_p = \sum_{j \in \mathcal{P}Divested\ instruments} EI_j^p + \sum_{j \in \mathcal{P}Remaining\ instruments} \underbrace{N_j}_{buy/sell} \underbrace{PI_j . \frac{1}{V_p}}_{Price\ fluctuations} .EI_{i(j)}$
What is the contribution of sector allocation and stock selection?	$EI_p = \sum_{j \in \mathcal{P}Divested\ instruments} EI_j^p + \sum_{j \in \mathcal{P}Remaining\ instruments\,(RI)} w_{RI} . w_{s(i(j)),RI} . w_{is(i(j)),RI} . EI_{i(j)}$
What is the contribution of sector inflation and emissions scopes?	$EI_p = \sum_j w_j . \underbrace{\frac{Prod_{i(j)}}{R_{i(j)}}} . \left(\frac{E1_{i(j)}}{Prod_{i(j)}} + \frac{E2_{i(j)}}{Prod_{i(j)}} \right)$ where $Prod_{i(j)}$ is the physical production (expressed in tonnes in our example) of the company, $E1_{i(j)}$ the company emissions on Scope 1, and $E2_{i(j)}$ on Scope 2.

For the fictitious portfolio, divestment accounts for most of the absolute emissions reduction, while reallocations and financial fluctuations have minimal impact. In contrast, company emissions increase overall (figure 8). From an extra-financial perspective, this model raises concerns, as company emissions rise despite the portfolio's emissions decline. Since divestment drives much of the reduction, ensuring its sustainability justification is crucial.[6] If the exclusion list is valid, the effect of legitimate divestments should be decomposed from other divestments.[7]

Effects of divestment and reallocation on emissions intensity

If absolute emissions have risen, this may be due to increased emissions intensity or company activity, such as market share growth. One approach to addressing this is by analysing portfolio emissions intensity, which can change due to shifts in instrument weights or company emissions intensity. Weight fluctuations result from buy/sell decisions or price changes.

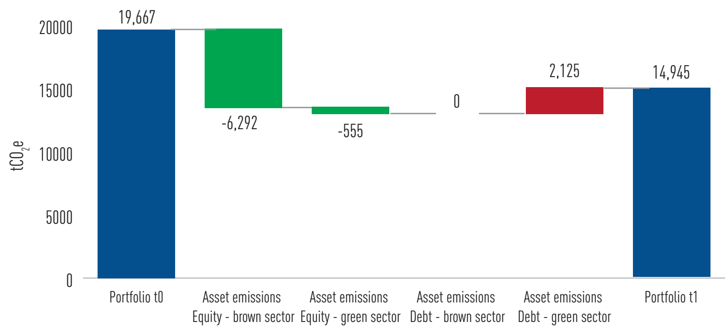
Unlike absolute emissions, portfolio and firm emissions intensity is declining,[8] indicating that the rise in absolute emissions was mainly due to increased activity (revenue – figure 9). The effects of other drivers align with the absolute emissions analysis: divestment – isolated here but potentially part of the quantity effect – remains the primary factor, followed by a slight upward impact from buy/sell decisions, while price fluctuations help reduce intensity.

Effects of sector allocation and stock selection on emissions intensity

The initial absolute emissions model identified sector contributions but did not clarify whether reductions resulted from decreased sector exposure or intra-sector reallocations. This fourth model separates sector allocation from stock selection while isolating the divestment effect, focusing only on remaining instruments[9] (figure 10a). In a context of significant price fluctuations, adjustments further distinguish the effects of quantity and price changes on these weights (figure 10b).

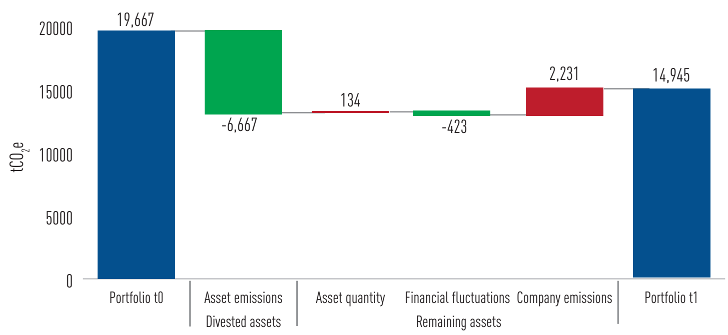
Even after accounting for divestment, the portfolio's intensity reduction is mainly driven by sector allocation, shifting from brown to green sectors. However, stock selection within sectors increases intensity, as GS-HI's weight rises relative to GS-LI. From a climate impact perspective, sector allocation may artificially reduce emissions by

7. Attribution of change in absolute emissions by asset class and sector



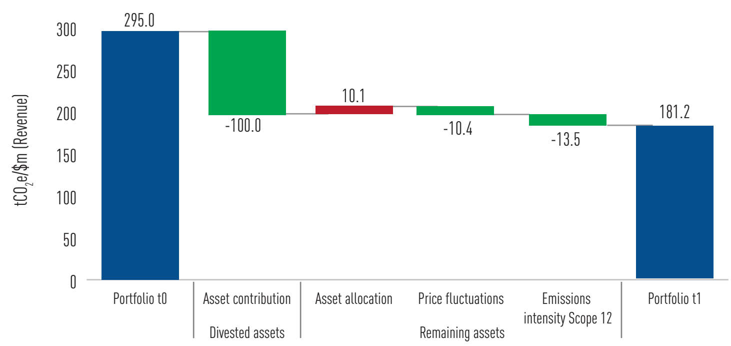
Note: Analysis of a fictitious portfolio using LMDI.

8. Attribution of change in absolute emissions by divestment, reallocation, financial fluctuations and company emissions



Note: Analysis of a fictitious portfolio using LMDI.

9. Attribution of change in intensity per revenue by divestment, allocation, price fluctuations and company intensity



Note: Analysis of a fictitious portfolio using LMDI.

6 Either due to the company's involvement in controversial activities or an unsuccessful engagement campaign.

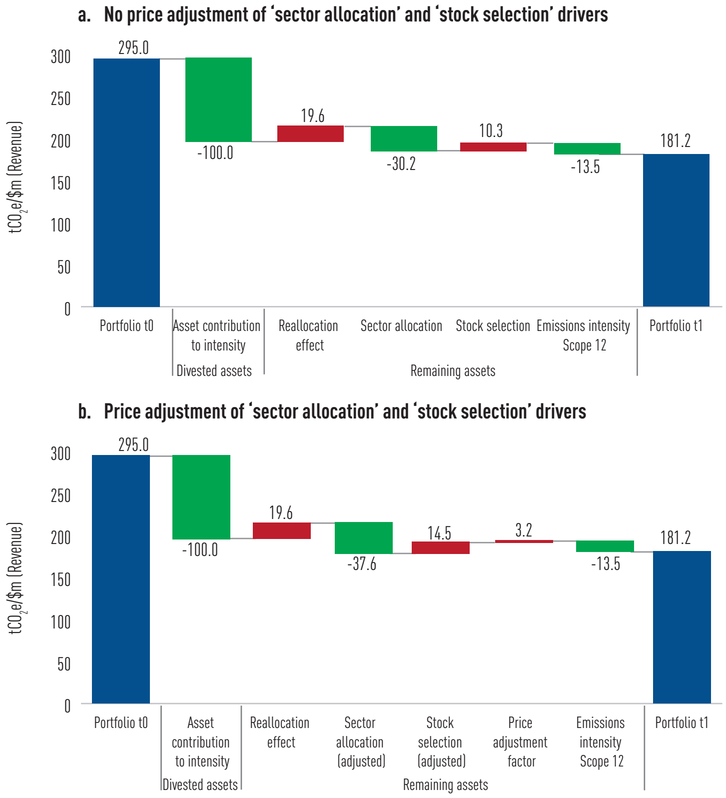
7 In this case, the 'divestment' effect will be decomposed as:

$\sum_{j\in\mathcal{P}_{Divested\ instruments}} E_j^P = \sum_{j\in\mathcal{P}_{Divested\ instruments\ in\ list}} E_j^P + \sum_{j\in\mathcal{P}_{Divested\ instruments\ not\ in\ list}} E_j^P$.

8 This results from BS-LI maintaining a constant intensity, while GS-HI and GS-LI show decreasing intensities.

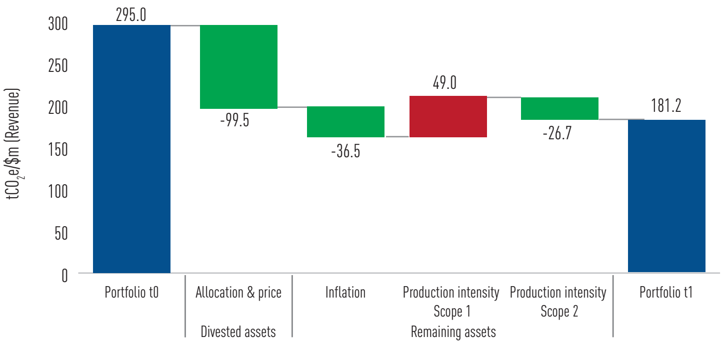
9 A driver capturing the weight change of remaining instruments relative to divested ones is introduced, isolating sector allocation and stock selection effects for retained stocks. Without this, BS-LI's sector allocation effect would be skewed by BS-HI's exclusion.

10. Attribution of change in intensity per revenue by divestment, sector allocation, stock selection and company intensity



Note: Analysis of a fictitious portfolio using LMDI.

11. Attribution of change in intensity by allocation, inflation and scope



Note: Analysis of a fictitious portfolio using LMDI.

lowering exposure to high-emission sectors and should not be prioritised.[10]

Effects of company emissions and inflation on emissions intensity
The first two models showed rising company emissions, with the third linking this to revenue growth, while emissions intensity declined slightly. However, monetary intensity is inflation sensitive. Adjusting for inflation clarifies whether intensity changes stem from production efficiency or inflation effects.[11] Specific drivers are also introduced for each emissions scope.

This last model finds inflation significantly reduced emissions intensity (per revenue), while physical intensity (eg, CO_2 per tonne of steel) rose. The decline in physical intensity is mainly from Scope 2 emissions, whereas Scope 1 emissions increased (figure 11). Since companies cannot control the local electricity mix, they have more leverage over Scope 1 emissions tied to operations. Differentiating production efficiency, inflation, and emissions scopes helps portfolio managers refine engagement strategies.

Reconciling the absolute emissions, intensity and footprint emissions metrics
The attribution models have been used to analyse different portfolio emissions, demonstrating the flexibility of the generalisation approach. Depending on the context, certain metrics may be more relevant than others. A key advantage of attribution analysis is its ability to explicitly link these metrics. Specifically, absolute portfolio emissions can be expressed in terms of intensity and footprint metrics. As presented before:

$$E_p = \sum_j \underbrace{E_j^p}_{\text{Absolute emissions (associated with instrument } j)}$$

Absolute emissions for each instrument can be calculated as the product of the portfolio value and the carbon footprint of the associated company.

$$E_p = \sum_j V_p, \underbrace{w_j \cdot \underbrace{\frac{E_{i(j)}}{EVIC_{i(j)}}}_{\text{Footprint}}}_{\text{Absolute emissions}}$$

Company emissions can be expressed as the product of the company's emissions intensity and revenue.

$$E_p = \sum_j V_p, \underbrace{w_j \cdot \underbrace{\underbrace{\frac{E_{i(j)}}{R_{i(j)}}}_{\text{Intensity}} . R_{i(j)} \cdot \frac{1}{EVIC_{i(j)}}}_{\text{Footprint}}}_{\text{Absolute emissions}}$$

Using this model, all drivers influencing absolute emissions, emissions intensity, and footprint become visible, allowing for a unified analysis of each metric's evolution.

Adjusting the portfolio's emissions footprint for EVIC inflation alters the EVIC driver's attribution results but leaves the effects of key investor-driven factors unchanged. Applying an inflation adjustment to the emissions footprint or using a model with an EVIC driver accounts for financial instrument price inflation, but combining both methods

10 The IIGCC (2023) recommends that net-zero benchmarks prioritise real-world 'organic' decarbonisation over 'paper' decarbonisation and supports a sectoral approach.
11 In our example, we use individual company production data. When unavailable, company revenues can be adjusted using a sectoral inflation factor.

adds no further value.

Conclusion

Since 2022, several attribution frameworks have emerged to clarify the emissions drivers in financial portfolios. This article examines their key differences and explores how they can be effectively combined.

Most frameworks focus on historical analysis of absolute emissions, emissions intensity, and equity portfolio emissions. Their identified drivers fall into four categories: data coverage, portfolio reallocation, economic and financial fluctuations, and company emissions.

Two methods attribute changes in emissions metrics: the Laspeyres indicators and the logarithmic mean Divisia index (LMDI). Laspeyres is preferred for two-driver models, while LMDI is better for multiple drivers, as it eliminates interaction terms.

The drivers in these frameworks complement each other rather than serve as substitutes. A flexible three-step model integrates them, allowing investors to assess the impact of asset class allocation, divestment, sector allocation, stock selection, price volatility, emissions scopes, company activity and inflation on portfolio emissions metrics.

By integrating drivers from existing frameworks, investors can better identify emissions changes, distinguishing between exogenous factors and those they can influence, either directly (eg, allocation, divestment, stock selection) or indirectly (eg, corporate emissions through engagement). Attribution analysis is thus critical for constructing and monitoring a climate investment strategy.

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Do ESG scores and ESG screening tell the same story?

Assessing their information overlap

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This study[1] examines the informational overlap between environmental, social, and governance (ESG) scores and ESG exclusionary screening strategies within equity portfolios.

Key takeaways

While ESG scores are widely used for integrating sustainability considerations in portfolio management, they may not fully align with exclusion criteria targeting companies engaged in controversial activities or behaviour.

By comparing the results of both approaches on a set of 417 indices, the analysis reveals that reliance on ESG scores alone omits a substantial proportion of companies that fail to meet 'do no harm' criteria.

However, the results show that exclusion strategies can enhance a portfolio's ESG score, suggesting a complementary role in achieving sustainable investment objectives.

Introduction

The Global Sustainable Investment Alliance (GSIA) defines sustainable investment as an "investment approach that considers environmental, social and governance (ESG) factors in portfolio selection and management" (GSIA [2021]). Under this broad definition, the volume of global sustainable investments reached $30.3trn in 2022, representing approximately 38% of all professionally managed assets. Within sustainable investment strategies, exclusionary screening, ESG integration[2] and engagement represent the most prevalent approaches. While these strategies may theoretically complement one another, in practice, they rely on diverse data sources which can lead to inconsistent outcomes. This study focuses on examining the relationship between exclusion screening, guided by 'do-no-harm' criteria, and ESG integration, guided by ESG scores.

Exclusion screening, historically the earliest practice within sustainable finance, remains widely adopted despite a recent slowdown (GSIA [2023]). The Financial Exclusion Tracker Initiative reports that exclusions currently emphasise climate-related concerns. For instance, the EU regulation on climate benchmarks mandates exclusion criteria concerning fossil fuel-related activities and adheres to the 'do-no-harm' principles embedded in the EU Taxonomy. In practice, investors implement these exclusion thresholds based on data detailing companies' operational activities (eg, revenue composition, energy mix) and behaviour (eg, controversies).

In contrast, ESG integration has gained momentum, driven by client preferences and regulatory pressure (GSIA [2023], PRI [2023]). Integrating ESG criteria is increasingly recognised as part of an investor's fiduciary duty and is a prerequisite for claiming alignment with sustainable objectives, as outlined in Articles 8 and 9 of the Sustainable Finance Disclosure Regulation (SFDR). In practice, ESG scores – whether proprietary or provided by external data providers – are the most common data source supporting this approach.

To clarify the relationship between exclusion screening and ESG integration, this study addresses the following questions:

- Do strategies based solely on ESG scores naturally shield investors from companies whose activities or behaviours may cause harm?
- When combined with ESG integration, do exclusion strategies improve ESG scores?

Data and method

These questions are explored through an analysis of the composition of 417 diversified indices from the Developed Europe and US investment regions, as of October 2024.

To capture the variety in exclusion practices – including themes, criteria and

1 For the original unabridged version of this paper, see: https://scientificportfolio.com/pdfs/2024-12-do-esg-scores-and-esg-screening-tell-the-same-story.pdf

2 Defined as the "consideration of ESG factors within an investment analysis and decision-making process with the aim to improve risk-adjusted returns" (GSIA [2023], 7).

thresholds, three distinct exclusion strategies, developed by Porteu de la Morandière, Vaucher and Bouchet (2025), are considered. The first strategy reflects consensus-based exclusion criteria among the largest 100 asset owners; the second includes additional climate criteria defined by the Paris-Aligned Benchmark (PAB) standards; the third excludes companies that contribute negatively to the United Nations Sustainable Development Goals (SDGs – see Appendix for details on the three strategies). In terms of weight excluded, the consensus and PAB screens have similar impacts for Developed Europe indices, while the SDG screen leads to significantly higher exclusions (figure 1).

ESG scores have been the subject of much debate and are known to vary widely across providers. Different providers often assign different scores to the same company or the same fund. For example, among S&P 500 companies, the average correlation between ESG ratings from six providers is less than 0.5 (Gibson Brandon et al [2022]). Furthermore, only 20% of funds deemed ESG-compliant by any one of the three major providers – Bloomberg, Morningstar or Refinitiv – are classified as sustainable by all three. At the company level, Berg, Koelbel and Rigobon (2022) show that the divergence in ESG scores is mainly explained by differences in the measurement of each of the underlying ESG attributes, but also by different attribute weights, and to a lesser extent by differences in the attributes included in the scope of these scores.[3] To account for this heterogeneity in ESG scores, this study uses a unique database provided by ValueCo that aggregates ESG scores from more than five asset managers for each equity issuer. ValueCo[4] specialises in collecting proprietary extra-financial assessments developed internally by asset managers to provide an ESG market view, similar to an ESG bid-offer system for financial markets.[5] Notably, companies and indices in the Developed Europe region generally have higher average ESG scores compared to those in the US region (figure 2).

1. Descriptive statistics related to ESG screens

a) Developed Europe	Indices (n = 130)	Benchmark companies (n = 406)	
ESG screen	Average weight excluded	Number excluded	Weight excluded
Consensus	12.5%	35	13.3%
PAB	15.3%	46	15.9%
SDG	55.2%	176	58.3%
b) US	**Indices (n = 387)**	**Benchmark companies (n = 467)**	
ESG screen	**Average weight excluded**	**Number excluded**	**Weight excluded**
Consensus	13.9%	54	143.3%
PAB	19.6%	68	17.5%
SDG	61.2%	213	68.7%

Note: This table shows, for each ESG exclusion strategy (ESG screen), descriptive statistics related to the stocks that do not meet the criteria defined by the screen. The second column from the left shows the average financial weight represented by these stocks in the indices for each region, while the third and fourth columns show the number of these stocks and their financial weight within the benchmarks for each region.

2. Descriptive statistics of ESG scores

a) Developed Europe		
Dimension	Average score (cap-weighted) of indices (n = 130)	Cap-weighted score of companies (n = 406)
ESG	59.8	58.4
E	56.0	53.0
S	56.9	55.1
G	68.7	66.5
b) US		
Dimension	**Average score (cap-weighted) of indices (n = 387)**	**Cap-weighted score of companies (n = 467)**
ESG	48.6	48.9
E	45.7	41.6
S	48.3	51.5
G	58.2	57.0

Note: This table shows, for each ESG score dimension, descriptive statistics related to the score of the stocks. The second column from the left shows the average financial cap-weighted score in the indices for each region, while the third and fourth columns show the cap-weighted score of the corresponding regional benchmark. The share of companies covered by scores – with a minimum of five independent ratings per company – is on average 97% for the Developed Europe indices and 94% for the US indices.

Limitations of ESG scores in identifying harmful companies

The first result from this study is that good ESG scores, whether at the company level or aggregated index level, are not sufficient to guarantee that a company's activities or behaviour align with the do no harm criteria. Although indices with the best aggregate ESG scores (those in the fourth quartile) typically contain fewer harmful stocks than those with lower ESG scores[6], a notable proportion of stocks within these high-scoring indices should still be excluded according to the three exclusion screens. For example, of the 97 indices with the best ESG scores in the US, 41 hold more than 8% of companies that are considered harmful according to the consensus criteria (by way of reference, the US benchmark contains 14% of such companies – figure 3).

These results are consistent when analysing the constituents of the regional benchmarks: the companies with the best ESG scores do not necessarily meet the do-no-harm criteria. In the Developed Europe benchmark, out of the 101 companies in the top quartile in terms of ESG score, nine companies (approximately 10%) fail to meet the criteria associated with the consensus screen. This discrepancy can be attributed to several factors.

- Firstly, most of these companies operate in the energy and utilities sectors, which face structural sustainability challenges and are often excluded from PAB-aligned portfolios. On the other hand, best-in-class ESG scoring approaches may identify leaders within these sectors and assign them high scores for performing better than their peers, even though they remain large carbon emitters.
- Secondly, ESG scores often take into account a broad range of factors, while PAB filters focus on climate-related metrics. Good performance or ambitious commitment on other environmental topics, or regarding social and governance challenges, may lead a company to get high ESG scores in spite of harmful practices and activities from a climate-focused point of view.

3 The respective contributions of 'measurement', 'scope' and 'weight' are 56%, 38% and 6%.

4 See https://www.valuecometrics.com/en

5 Scores are normalised between 0 and 100. Unless specifically indicated otherwise, the scores used in this study are the median scores for each issuer.

6 The difference between the top-quartile (q4) indices and those in the second and third quartiles (q2, q3) is not statistically significant for Developed Europe indices.

3. Impact of exclusion according to the ESG score quartile at the indices level and at the benchmark company's level

a) Developed Europe

Quartile	Average score of indices	Average weight excluded of indices (Indices (n = 130))			Quartile	Average score of benchmark companies	No of benchmark companies excluded (Benchmark (n = 406))		
		Consensus	PAB	SDG			Consensus	PAB	SDG
q1 (n=33)	55.6	13.4	24.4	60.1	q1 (n=102)	45.9	19.0	22.0	54.0
q2 (n=32)	59.1	11.3	13.2	56.8	q2 (n=101)	57.0	4.0	8.0	38.0
q3 (n=32)	60.8	6.8	8.5	55.0	q3 (n=102)	62.1	3.0	5.0	41.0
q4 (n=33)	**63.7**	**8.1**	**8.8**	**49.2**	**q4 (n=101)**	**68.8**	**9.0**	**11.0**	**43.0**

b) US

Quartile	Average score of indices	Average weight excluded of indices (Indices (n = 387))			Quartile	Average score of benchmark companies	No of benchmark companies excluded (Benchmark (n = 467))		
		Consensus	PAB	SDG			Consensus	PAB	SDG
q1 (n=97)	42.6	20.7	35.2	68.6	q1 (n=117)	32.4	40.0	52.0	84.0
q2 (n=96)	48.1	14.0	18.3	61.1	q2 (n=117)	47.3	5.0	7.0	42.0
q3 (n=96)	50.1	11.5	15.3	59.9	q3 (n=116)	53.7	2.0	2.0	42.0
q4 (n=97)	**53.6**	**7.0**	**8.1**	**55.1**	**q4 (n=117)**	**62.1**	**7.0**	**7.0**	**44.0**

Note: This table shows the evolution of the weight of stocks that do not meet the 'do no harm' criteria associated with the three screens, as a function of the ESG score. The left columns show the average weight of these stocks for different indices grouped by quartile according to their EGS score (indices in q4 are those with the highest scores), while the right-hand columns do the same for benchmark stocks.

- Finally, some of these companies are actively transitioning towards more sustainable practices, which are valued in their ESG scores, but still have fossil fuel exposure excluded under PAB. The forward-looking dimension of ESG scores may inflate the results of companies showing steady and credible improvements in their practices before they actually meet the criteria to be included in PAB-aligned portfolios.[7]

The second result of this study is that targeting companies with the lowest ESG scores within these benchmarks does not allow for proper identification of companies with harmful activities or behaviours. Within the Developed Europe benchmark, a selection of the 35 companies with the lowest ESG scores – corresponding to the number of exclusions under the consensus screen – reveals that only 12 companies overlap with those identified by the consensus filter. Consequently, an exclusion approach based on ESG score rankings alone would fail to capture roughly two-thirds of the companies that are deemed to have a negative impact according to the consensus criteria.

Exclusion of harmful companies tends to improve ESG score

As outlined in the previous section, ESG integration based solely on ESG scores may not adequately ensure alignment with a 'do no harm' principle. This calls for an examination of the potential compatibility between ESG integration and exclusionary screening approaches. In particular, it is crucial to assess the impact of exclusions on strategies aimed at maximising a portfolio's ESG score.

The analysis suggests that excluding harmful stocks does not hinder such strategies. On the contrary, exclusions tend to have a positive effect on the aggregate ESG score. Applying the three exclusion screens to the set of indices, followed by a proportional reweighting, leads to a significant increase in their weighted average ESG scores (figure 4).

These results are consistent when analysing the constituents of both benchmarks. Companies that do not meet the criteria set by the consensus and PAB screens typically have ESG scores significantly below the average, a trend that is especially pronounced among US companies[8] (figure 5).

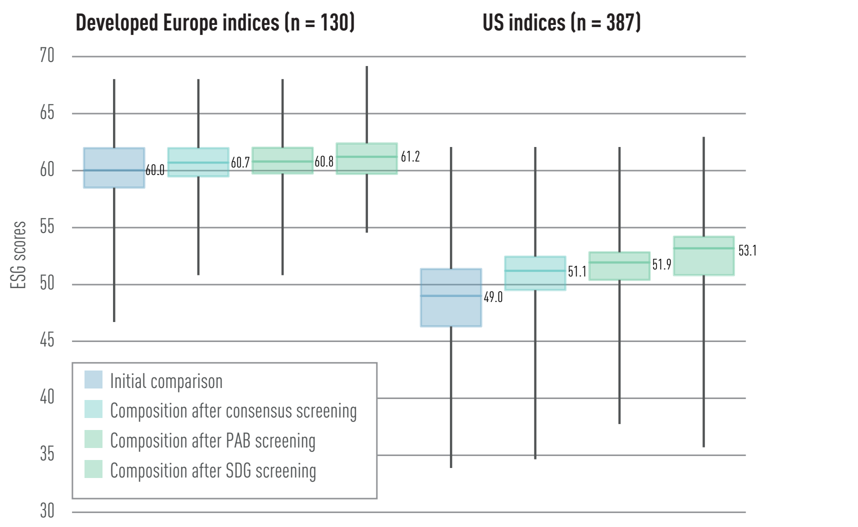
However, the impact of exclusions on the aggregate ESG score depends on the initial level of the aggregate ESG score. For Developed Europe, indices already exhibiting a high ESG score (in the fourth quartile q4), exclusions have no significant positive effect (figure 6).

As mentioned in the previous section, certain companies with high ESG scores are excluded, potentially reducing the aggregate ESG score of portfolios concentrated on these stocks. In our index universe, only two indices are subject to a (non-significant) reduction in their aggregate ESG score.

Conclusion

This study shows that ESG integration relying solely on ESG scores does not ensure alignment with the 'do no harm' principles within portfolios. The analysis of diversified indices from Developed Europe and the US demonstrates that exclusionary screening based on ESG criteria identifies companies engaging in

4. Evolution of the distribution of ESG scores of indices after exclusion



Note: This graph shows the evolution of the ESG scores of the indices for each region, after different ESG exclusion strategies (ESG screens). Whatever the ESG screen considered, the improvement in the ESG score is significant.

7 Companies with higher ESG scores also tend to have more divergent scores (see Appendix). However, the test results remain similar when using the score from the first quartile of the score distribution for a given company.
8 In contrast, companies excluded by the SDG filter tend to have ESG scores close to the benchmark average.

5. Score of benchmark constituents with controversial activities or behaviour

a) Developed Europe				
Score	Average score of constituents	Average of constituents that do not meet the criteria		
		Consensus	PAB	SDG
ESG	**58.4**	**51.2**	**52.5**	**57.1**
E	53.0	51.7	52.5	53.3
S	55.1	49.5	51.2	53.7
G	66.5	67.8	66.8	67.0

a) US				
Score	Average score of constituents	Average of constituents that do not meet the criteria		
		Consensus	PAB	SDG
ESG	**48.8**	**33.1**	**33.4**	**44.8**
E	41.6	40.9	41.1	40.6
S	51.5	51.3	48.9	48.9
G	57.0	56.8	55.4	55.4

Note: This table shows the average score (ESG, E, S and G) of stocks that do not meet the 'do no harm' criteria of the different ESG screens within each regional benchmark. Stocks corresponding to companies that do not comply with the consensus and PAB screens have significantly lower ESG scores than the other benchmark constituents.

6. Impact of exclusion on the weighted average scores of the indices by quartile

a) Developed Europe		Indices (n = 130)		
Quartile	Average score of indices	New weighted average indices scores after exclusion		
		Consensus	PAB	SDG
q1 (n=33)	55.6	58.3	58.6	59.0
q2 (n=32)	59.1	60.3	60.4	60.8
q3 (n=32)	60.8	61.1	61.1	61.6
q4 (n=33)	63.7	63.6	63.6	63.7

b) US		Indices (n = 387)		
Quartile	Average score of indices	New weighted average indices scores after exclusion		
		Consensus	PAB	SDG
q1 (n=97)	42.6	46.2	47.7	48.7
q2 (n=96)	48.1	50.4	51.2	52.1
q3 (n=96)	50.1	51.7	52.4	53.6
q4 (n=97)	53.6	54.2	54.4	55.6

Note: This table shows the changes in the cap-weighted average ESG score of indices after different ESG exclusion strategies, according to the starting ESG score of these indices (by quartiles). For Developed Europe indices already exhibiting a high ESG score (q4), none of the exclusion strategies have a significant effect.

harmful activities or behaviours that ESG scores alone may fail to identify. However, these two approaches are not incompatible. Applying exclusion screens generally improves the weighted average ESG scores of indices, indicating that exclusions can complement ESG integration by refining portfolio quality without detracting from ESG performance. These findings highlight the potential for exclusionary practices to reinforce ESG integration, supporting the creation of more sustainable and resilient investment portfolios. The natural next step would be to anticipate the financial impact of such exclusions, a topic which is covered in Porteu de la Morandière, Vaucher and Bouchet (2025) where they find that applying exclusions either based on consensus criteria or climate criteria has a relatively low impact on the financial risk profile of indices and that this impact can be further reduced with an optimised reallocation.

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Appendix – ESG exclusion screens

The consensus screen is based on an analysis of the exclusion policies of the world's 100 largest asset owners. This analysis resulted in a set of four criteria most frequently used by asset owners that define the screen: the controversial weapons industry, the tobacco industry, the coal industry and controversies related to the United Nations Global Compact (UNGC) 10 principles.[9]

The PAB screen is based on the minimum standards[10] that define EU Climate Transition Benchmarks and Paris-aligned Benchmarks. In addition to minimum reduction of greenhouse gas footprint (not considered in this article), these standards define exclusion criteria related to climate change (coal and fossil fuels industries) and to sustainable development (tobacco and controversial weapons industries, controversies related to the UNGC principles).

Finally, the sustainable development goals or SDG screen is based on the United Nations Sustainable Development Goals framework adopted in 2015. This framework consists of 17 goals and 169 targets to be achieved by 2030, covering social, environmental, and economic issues. The exclusion criteria of the corresponding screen cover any activities or behaviour that would hinder the achievement of these goals and targets (the complete methodology for the three screen is available in Porteu de la Morandière, Vaucher and Bouchet [2025]).

7. Dispersion of ESG scores

a) Developed Europe

Quartile	Average ESG scores dispersion of the companies in the benchmark	Average ESG scores dispersion of the companies excluded		
		Consensus	PAB	SDG
q1	77.1	74.8	74.9	76.7
q2	78.6	76.5	76.4	77.1
q3	79.0	74.5	73.0	76.4
q4	**79.3**	**81.0**	**81.0**	**80.0**

b) US

Quartile	Average ESG scores dispersion of the companies in the benchmark	Average ESG scores dispersion of the companies excluded		
		Consensus	PAB	SDG
q1	84.8	83.4	84.1	85.1
q2	76.8	76.4	77.4	75.5
q3	76.2	83.8	83.8	77.2
q4	75.4	76.1	76.1	76.1

Note: This table shows the dispersion of ESG scores for benchmark constituents according to their initial ESG score (stocks are grouped by quartiles), and according to whether they are excluded by different ESG screens (right columns). The dispersion score is expressed between 0 (no dispersion) and 100 (maximum dispersion) and corresponds to the deviation from the average of the scores given by the different asset managers.

ESG score dispersion

Within the EU benchmark, companies with high ESG score – including those that are excluded by the different ESG screens – exhibit a high dispersion in their ESG scores (figure 7), potentially indicating that while these companies perform well in most ESG areas, certain aspects of their operations are heterogeneously penalised by the different asset managers rating scales. Another interpretation could be a misalignment between the reporting and the actual performance of these companies on ESG topics. When they under-report or, on the contrary, indulge in greenwashing, ESG data providers have different methodologies to estimate the gaps or penalise misleading claims. The data sources employed by investors for their responsible investment strategy may therefore introduce divergence in the resulting scores. This is not the case for the US index, where ESG score dispersion is already high across the board, reflecting broader variability in how companies are evaluated by the different asset managers.

9 The 10 principles are available at: https://unglobalcompact.org/what-is-gc/mission/principles

10 Commission Delegated Regulation (EU) 2020/1818.

Do ESG exclusions have an effect on portfolio risk and diversification?

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Exclusion/negative screening is the most popular methodology used to integrate environmental, social and governance (ESG) criteria into investment strategies. It consists of excluding instruments issued by companies that do not meet the criteria defined in the manager's investment policy. This method is often applied in passive investment strategies that combine exclusion criteria with index replication. In this article (a summary of a recent research paper[1]), we examine the impact of exclusion policies on the financial risks of 493 indices from Developed Europe and the US. To address varying ESG criteria, we built three screens: one based on consensual criteria among asset owners, another incorporating additional climate criteria, and a third eliminating companies negatively impacting any United Nations Sustainable Development Goal. The first two screens show limited impact on index risks, especially when using optimised reallocation.

Key takeaways:

On a sample of 128 European indices, the application of our ESG screens leads to an average excluded weight of 9%, 10% and 58% for our consensus, climate and SDG screens, respectively; on a sample of 365 US indices, it results in an average exclusion of 19%, 23% and 67%, depending on the screen.

Applying ESG screens with a naïve (pro rata) reallocation method results in a median tracking error between 0.9% and 4.7%, varying by screen and region. Sector deviations are most significant in the energy and utility sectors. Exclusions increase exposure to the Fama and French (2015) 'profitability' factor while slightly reducing exposure to 'investment' and 'value' factors. Using an optimised reallocation method reduces the tracking error by 0.3% and 1.6% and minimises factor exposure deviations.

ESG screens often reduce carbon footprint. With naïve reallocation scheme, reductions can reach up to 54% after PAB screening in the US sample. However, this reduction does not occur when using optimised reallocation.

Introduction

Exclusion, the oldest practice in sustainable finance (Schueth [2003]), remains very popular, with about $3,840bn of assets under management (AUM) subject to negative screening, and $1,807bn subject to norm-based screening, out of $30,321bn in total sustainable AUM (GSIA [2023]). Despite variations in motivation, criteria and thresholds, exclusion remains a foundational sustainable strategy. Based on a review of the academic literature, Bouchet and Safaee (2024) highlight that the main building blocks that investors ought to consider – themes, levers (including exclusion, allocation and engagement) and data – are interdependent and propose four families of coherent sustainable investment strategies. Although each strategy targets a specific type of extra-financial impact, all incorporate exclusion (figure 1). This study focuses on exclusions based on environmental, social and/or governance (ESG) criteria that can contribute to these strategies.

Exclusion reduces a company's access to capital, raising its market-implied cost of equity and pressuring it to reform if the cost of change is lower than the share price loss[2] (Heinkel et al [2001], Pástor et al [2021], De Angelis et al [2022]). The effects of exclusion are also indirect: Bergman (2018) highlights the public discourse shift over the low-carbon transition and Braungardt et al (2019) show the positive effects of the divestment movement on effective climate policy development. Bouchet and Safaee (2024) conclude that exclusion is relevant in three main situations: for consensus non-sustainable activities such as human rights violations, when other levers such as shareholder engagement have failed, or when it is a moral imperative for investors.

Whatever the extra-financial motiva-

1 Porteu de La Morandière, A., B. Vaucher and V. Bouchet (2024). *Do Exclusions Have an Effect on the Risk Profile of Equity Portfolios?* Scientific Portfolio Publication, September.

2 Bouchet and Safaee (2024) highlight that companies may grow without relying on equity markets, challenging this mechanism.

1. Exclusion as a foundation for coherent sustainable strategies

Strategy	Targeted companies	Themes	Levers: Exclusion	Allocation	Shareholder engagement & field building
Sustainable	Company behaviour and activities 'do no harm' to any of the SDGs	All	**Covering all SDGs, based on revenues, metrics, controversies**	Optimising risk and return under exclusion constraints	Publication of exclusion list
Transition	Company behaviour and activities 'do no harm' to certain SDGs but where change is possible	Specific	**Companies not prioritised for engagement + Companies where engagement has failed**	Optimising risk and return under exclusion and sustainability exposure (min/max share of 'transition' companies	Systematically engaging on issues related to the specific theme chosen Publication of targets, engagement outputs and exclusion list
Solutions	Company activities contribute positively to specific SDGs	Specific	**Covering all SDGs, based on revenues, physical metrics, controversies**	Optimising risk and return under exclusion and sustainability exposure (minimum share of 'positive contribution companies'	Focusing on enagement related to activities (strategy, investments)
Ethical	Company behaviour and activities are in line with ethical choices	All	**Based on subjective preferences**	Optimising risk and return under exclusion constraints	

This table outlines four coherent sustainable equity strategies. The sustainable strategy ensures portfolio alignment with companies that 'do no harm' on environmental and social issues. The transition strategy seeks to reform companies with negative impacts. The solutions strategy prioritises investments in companies addressing specific sustainability challenges. The ethical strategy aligns investments with personal or religious values.
Source: Bouchet and Safaee (2024)

tion, asset owners need to anticipate the financial impact of ESG exclusion. However, the existing literature presents contradictory results. The lack of consensus on the relation between ESG exclusion and financial performance might be explained by differences in sample characteristics (region, period, size) and the diversity of exclusion criteria. This is supported by Plagge (2023), who shows that the direction of the financial impact of ESG exclusions on portfolio returns depends on both the exclusion criteria and the region sample to which they are applied. More recently, Porteu de la Morandière et al (2024) analysed the effects of applying some climate-related exclusion criteria on fund risks rather than their short-term performance, arguing that the fund's risk profile is responsible for its long-term performance, and should thus be a primary concern for asset owners. Focusing on a sample of sustainable funds according to the European Union (EU) sustainable finance disclosure regulation (SFDR), their results suggest that excluding climate-related controversial stocks would have a limited impact on the funds' tracking error, sector exposure or factor exposures.

Our research aims to extend the work of Porteu de la Morandière et al (2024) on two levels. Firstly, we include both conventional and sustainable instruments with a sample of 493 indices domiciled in Europe and the US. Secondly, the exclusion criteria are not limited to climate change-related activities but cover broader ESG issues. Given the complexity of ESG criteria, we define three exclusion screens, with increasing impacts, that correspond to common sustainable investment policies. The first screen, termed consensus, involves consensus exclusion criteria; the second screen incorporates additional climate net criteria defined in the Paris-aligned Benchmarks (PAB) standards; the third screen excludes stocks that contribute negatively to Sustainable Development Goals (SDGs).

We find that ESG screening excludes 10-60% of weights in 128 European indices and 20-70% of weights in US indices. A naïve (pro rata) reallocation results in a median tracking error of 0.9-4.7%, with a 1.5% increase per 10% of excluded weights. Sector deviations occur mainly in energy and utilities. ESG exclusions tend to increase exposure to the profitability factor while slightly reducing exposure to investment and value factors, depending on the screen and the sample region. The reallocation method significantly impacts tracking error and factor deviations. The optimised reallocation method lowers median tracking error by 0.3-1.6% and reduces factor deviations. With this approach, every 10% of excluded weights increases tracking error by 1.1%, compared to 1.5% in naïve reallocation. ESG screening followed by a naïve reallocation reduces carbon footprint (up to 54% after the PAB screening on the US sample) while the ESG screening followed by an optimised reallocation has no significant impact on carbon footprint reduction.

These results suggest that reducing the investment universe to build a sustainable index can lead to a relatively low impact on its financial risk profile, which can be further reduced with an optimised reallocation method. However, if the strategy is to reduce its carbon footprint, the optimised reallocation should be constrained to reduce risk while maintaining maximum carbon footprint reduction.

Data and model

We analyse 493 indices using three ESG screens, assessing tracking error, sector deviations, and risk factor exposure under two reallocation methods: naïve (pro rata) and optimised. Tracking errors are evaluated using a covariance matrix based on stock returns from December 2018 to December 2023.

Sample of financial instruments
Our sample includes 128 developed European indices (208 equities in average) and 365 US indices (306 equities in average), selected from an initial sample of 517 indices.[3] Indices were excluded if they had less than a year of historical data, over 1% exposure to emerging markets or incomplete composition covering under 85% of the capital invested.

Environmental, social, and governance screens
We define three ESG screens reflecting investor strategies. The consensus screen, based on the policies of the 100 largest asset owners, excludes weapons, tobacco, coal and controversies related to the United Nations Global Compact (UNGC) 10 principles.[4] The PAB screen follows EU Climate Transition and Paris-aligned Benchmarks and excludes fossil fuels and industries misaligned with sustainable development. The SDG screen aligns with the UN's 17 Sustainable Development Goals (SDGs) and excludes activities that hinder their achievement.

Risk metrics and sustainability indicator
We assess the impact of ESG exclusions using tracking error, sectors deviations, and deviations in exposure to Fama-French (2015) risk factors, including momentum. Additionally, we analyse their effect on portfolio carbon footprint.

3 We approximate the index compositions by using those of ETFs that closely track them
4 The 10 principles are available at: https://unglobalcompact.org/what-is-gc/mission/principles

Naïve and optimised reallocation
We apply two methods to reallocate the weights of the excluded stocks. First, the naïve method corresponds to a pro rata reweighting of the index's remaining stocks.[5] This method assumes that an investment manager sells the controversial equities and reinvests in the remaining equities proportionally to their initial weight.

Second, the optimised method relies on a tracking error minimisation between the original portfolio w_{old} and the new portfolio w_{new}. The reallocation is the solution to the minimisation program:

$$w_{new} = argmin_w \left(w - w_{old}\right)^T \Omega \left(w - w_{old}\right)$$

using a Ledoit and Wolf (2003) normalised covariance matrix (Ω) for ex-post tracking error estimation.[6] Portfolios remain long-only with equal capital investment before and after reallocation. The strategy reduces the impact of the ESG exclusions on the risk of the portfolio by reinvesting in stocks with similar risk profiles to excluded equities.

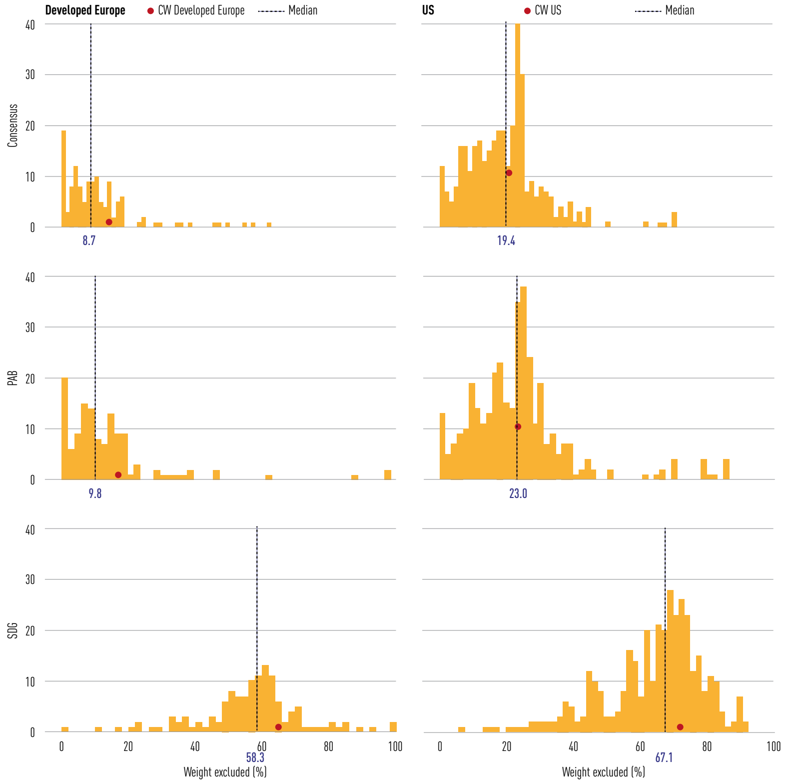
Results
This section presents the impact of ESG screens on excluded index weights, followed by their effects on risk profiles, including tracking error, sector deviation, factor exposure under naïve reallocation. We then show how optimised reallocation mitigates these effects and examine the varying impact of ESG exclusions on carbon footprint depending on the reallocation method.

Excluded weight of the indices
The impact of excluded weight varies by region (Developed Europe, US), and ESG screen (consensus, PAB, SDG). In Developed Europe, the consensus and PAB screens exclude a median of 9%, while the SDG screen excludes 58%. In the US, the consensus and PAB screens have twice the impact (20% median exclusion), while the SDG has a similar effect (67% – figure 2).

The impact varies by index theme (ESG, energy, utilities or other). Energy and utilities indices are most affected by the consensus and PAB screens due to fossil fuel-related exclusions. ESG indices are less impacted by these screens but are not shielded from the SDG screen, which excludes stocks beyond common ESG strategies. This suggests most ESG indices do not fully align with all SDGs (figure 3).

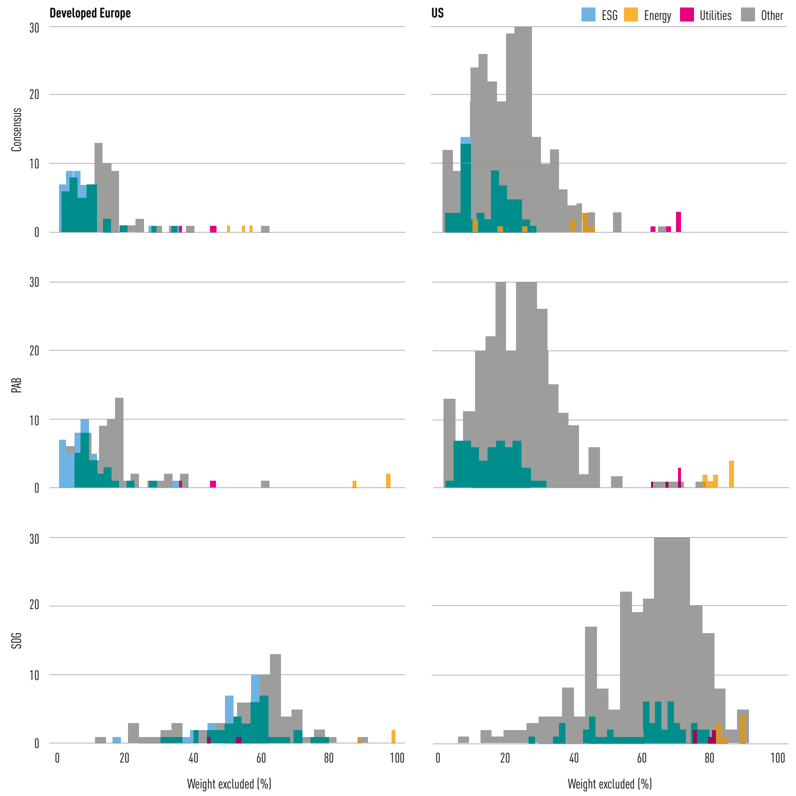
5 During reallocation, the fund's equity portion remains constant to maintain tracking error and factor exposure consistency. If 15% of a fund's 85% equity allocation is excluded, it is proportionally redistributed across the remaining 70% while preserving the total equity allocation.
6 All prices are in US dollars.

2. Distribution of indices weight excluded by screen and region



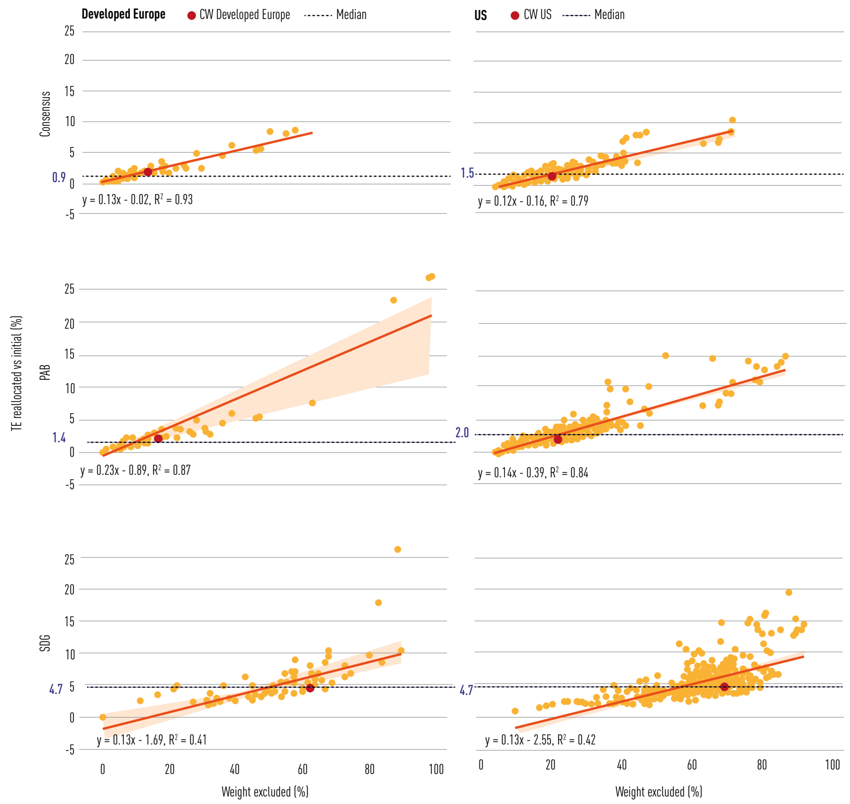
Source: Authors' calculation. The red marks represent the reference index for each region: the 410 largest companies (Developed Europe) and the 500 largest companies (US), both weighted by market capitalisation.

3. Distribution of indices weight excluded by screen, region and type



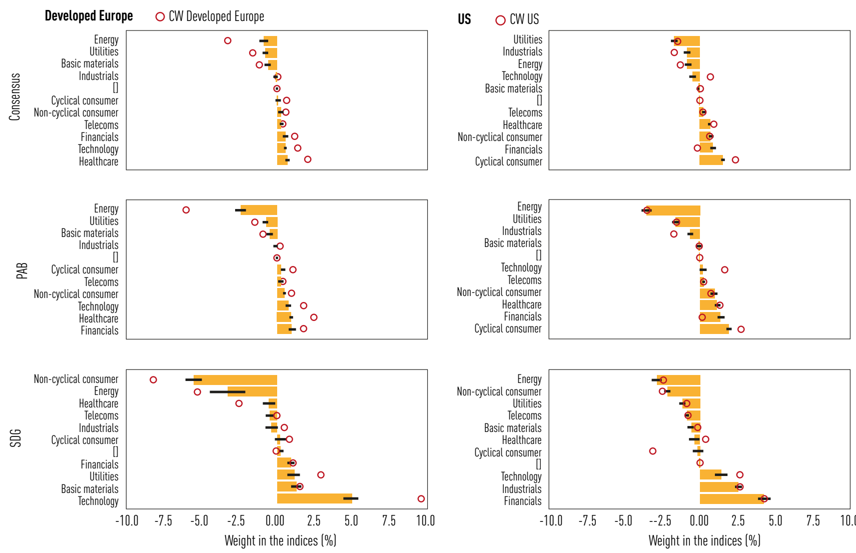
Source: Authors' calculation. The index themes are classified based on their names. The ESG category includes indices containing terms like ESG, screen, climate, transition, change, SRI, PAB, sustainability.

4. Impact of ESG exclusions on the tracking error between the screened and original index portfolio (naïve reallocation)



Source: Authors' calculation. Note: Tracking errors are calculated using a Ledoit and Wolf (2003) normalised sample covariance matrix.

5. Impact of ESG exclusions on sector deviations after naïve reallocation



Source: Authors' calculation. Note: The yellow bars represent the distribution mean, while black bars represent the standard error of the mean, calculated as the standard deviation divided by the square root of the sample size. This measures the dispersion of sample means around the population mean.

Impact of ESG exclusions on the risk profile of indices with naïve reallocation

ESG exclusion followed by naïve reallocation introduces tracking error. For Developed Europe indices, the median tracking error is 0.9% for the consensus screen and 4.7% for the SDG screen. In the US, where exclusions are higher, the impact is greater, with tracking error ranging from 1.5% (consensus screen) to 4.7% (SDG screen). Across regions and screens, tracking error increases relatively linearly with exclusions. Each additional 10% in excluded weight raises tracking error by about 1.5% (figure 4).

The impact of ESG exclusions on tracking error relative to the regional cap-weighted benchmark is uncertain. The median increase is 0.2% for the consensus screen (Developed Europe and US) and up to 2.3% for the SDG screen (Developed Europe, 1.7% for US). Unlike tracking error relative to the initial index, the relationship between excluded weight and tracking error change is not significantly increasing, likely due to the wide distribution of the initial tracking errors.

The impact of ESG exclusions on the tracking error, relative to both the initial index and benchmark, can be explained by sector and factor exposure deviations.

Sector deviations are most pronounced in energy and utilities across all regions and screens, with SDG screening also affecting the non-cyclical consumer sector. These deviations stem from fossil-fuel exclusions and criteria related to the environment, human rights and ethical controversies. However, deviations do not scale linearly with excluded weight. For example, in Developed Europe, the PAB screen excludes 10% of weight with a 2.5% median sector deviation, while the SDG screen excludes 60% with only a 5% deviation. Positive sector deviations result from naïve reallocation, where sectors with higher initial weights experience the largest increases.

ESG exclusions tend to increase exposure to higher 'profitability' stocks while reducing exposure to 'investment' and 'value' stocks across regions and screens. Excluded stocks are typically more exposed to 'value' and 'investment' factors and less to 'profitability' than the overall index, shifting the screened index's factor composition. These results align with Porteu de la Morandière et al (2024) and are statistically significant, confirming a consistent impact on indices.

Impact of ESG exclusions on the risk profile of indices with optimised reallocation

The impact of ESG exclusions on index risk is limited for the consensus and PAB screens under naïve reallocation, with median tracking errors of 0.9% (Developed Europe) and 1.5% (US). However, indices heavily weighted in affected sectors can see tracking errors exceed 10%, particularly under the PAB screen (2% of Developed Europe and 3% of US indices). The SDG screen has a greater effect, with a median tracking error of 4.7%.

Using the optimised reallocation method significantly reduces the tracking error and factor deviations but does not always mitigate sector deviations. The ability to materially reduce factor exposure deviations is a particularly welcome benefit of the optimised reallocation method and aligns with Plagge (2023), who found no significant alphas from ESG exclusions once Fama and French (2015) factors were controlled. Investors with fiduciary duties may favour optimised reallocation for minimising ESG exclusions' impact on long-term expected returns.

For Developed Europe indices, optimised reallocation reduces tracking error by -0.3%[7] (consensus screen) and -1.6% (SDG screen) compared naïve reallocation (-0.5% to -1.4% for US indices – figure 7). The relationship between excluded weight and tracking error also weakens: with each 10% exclusion increasing tracking error by 1.2% versus 1.5% under naïve reallocation. These reductions primarily stem from lower factor exposure deviations (figure 8), while sector deviations remain largely unchanged.

Impact of ESG exclusions on the carbon footprint of indices

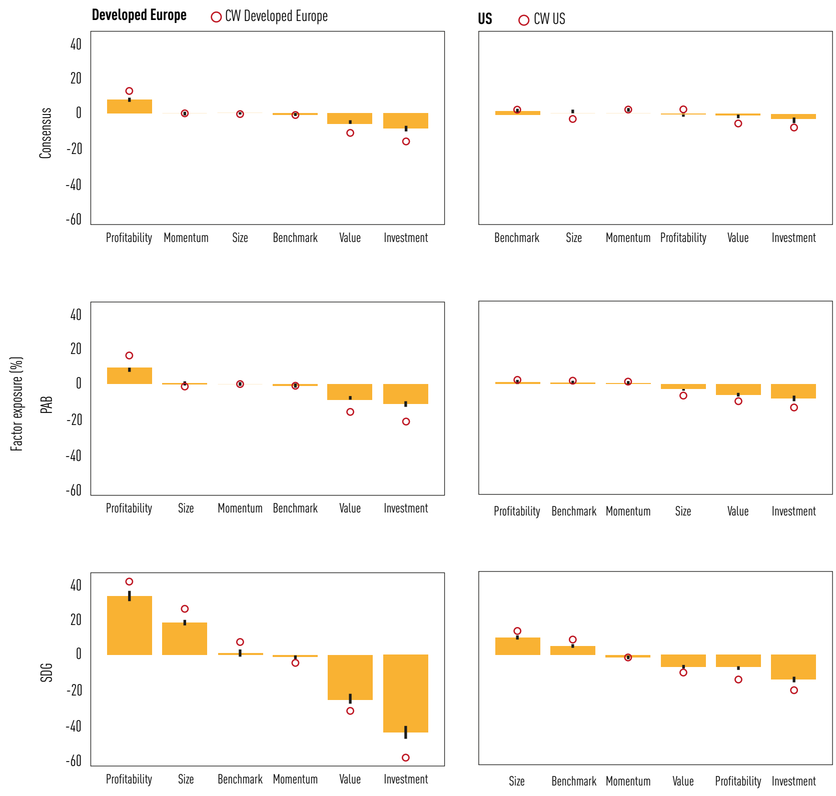
Environmental exclusions tend to reduce portfolio weighted average carbon footprint with naïve reallocation, but not necessarily with optimised reallocation.

Naïve reallocation under the consensus and PAB screens reduces portfolio carbon footprint reduction consistent with their coal and fossil fuels exclusion criteria. For Developed Europe, reductions are 22% (Consensus) and 29% (PAB), while US reductions are 30% and 54%. These reductions are mostly explained by sector deviations (energy and utilities), which might not be the most efficient way to decarbonise indices (Bouchet [2023]). For a 'transition' or 'solutions' investment strategy, this lever of exclusion should be supplemented by other allocation constraints designed to guarantee a minimum of sustainable exposure (figure 1).

The SDG screen does not significantly reduce carbon footprints (figure 9). While it includes climate-related criteria like the

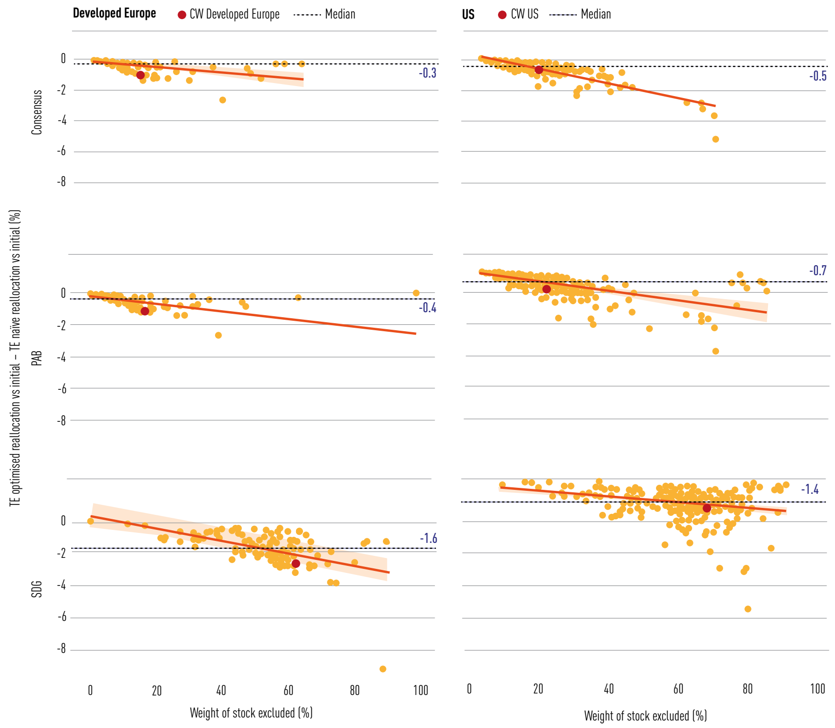
7 Median.

6. Impact of ESG exclusions on factor deviations after naïve reallocation



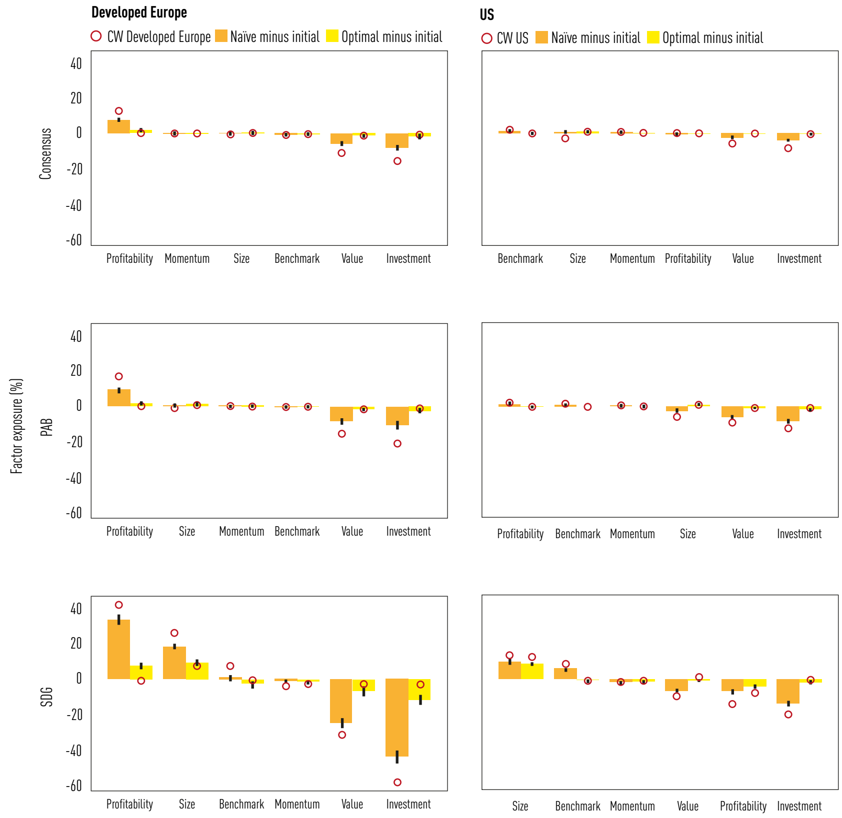
Source: Authors' calculation. Note: The orange bars represent the distribution mean; black bars represent the standard error of the mean, measuring sample mean dispersion around the population mean.

7. Reduction in tracking error between optimised and naïve reallocation



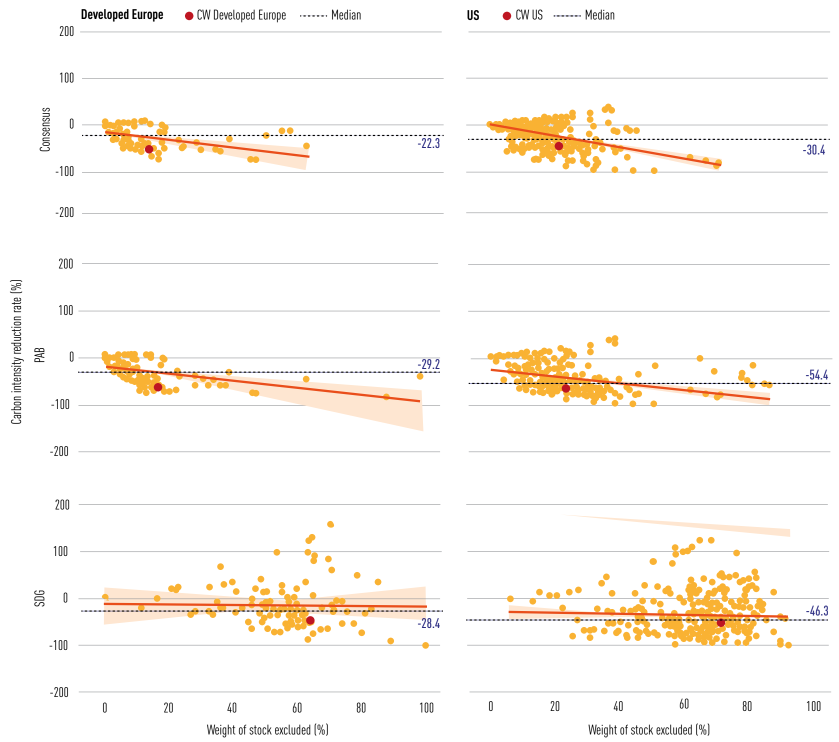
Source: Authors' calculation. Note: Annualised tracking errors of reallocated indices versus initial indices, using a Ledoit and Wolf (2003) normalised covariance matrix.

8. Reduction in factor factor deviation between optimised and naïve reallocation



Source: Authors' calculation. Note: Black bars represent the standard error of the mean, measuring sample mean dispersion around the population mean.

9. Reduction of the carbon footprint of screened indices after the naïve reallocation by weight of stock excluded



Source: Authors' calculation. Note: Annualised tracking errors of reallocated indices versus initial indices, using a Ledoit and Wolf (2003) normalised covariance matrix.

PAB screen, its broader social and governance exclusions also remove companies with very low carbon intensities, leading to inconsistent impact across indices.

Optimised reallocation reduces the financial impact of ESG exclusions but results in a smaller carbon footprint reduction than naïve reallocation. For example, US indices with the consensus screen see a 30% carbon footprint reduction with the naïve reallocation but only 22% with the optimised reallocation. This occurs because optimised reallocation tends to replace excluded stocks by their closest equivalent in terms of risk profile, while the naïve scheme favours the largest capitalisations, which are in the technology and financials sectors, two sectors that have much lower carbon footprint than the benchmark average. Thus, optimised reallocation can increase exposure to carbon-intensive sectors. For example, 50% of the Developed Europe indices screened with the PAB screen followed by an optimised reallocation are more exposed to the energy sector than these indices after a naïve reallocation.

Conclusion

Excluding stocks of companies involved in controversial activities is common in sustainable investment strategies, but asset-owners must anticipate the financial impact of such exclusions. This article explores the effects of ESG exclusions on financial risks.

We propose three ESG exclusion screens with increasingly stringent criteria: the consensus screen based on common asset-owner criteria; the PAB screen aligned with EU PAB standards; and the SDG screen tied to the UN's 17 Sustainable Development Goals. We analyse the impact of these ESG exclusion screens on tracking error, sector allocation, risk factor exposure, and carbon footprint across 493 Developed Europe and US indices. The analysis uses two reallocation methods: a naïve method based on initial weights and an optimised method minimising tracking error.

The three ESG screens result in excluded weights ranging from 10% to 70%, varying by screen and region. A naïve reallocation yields a median tracking error of 0.9% to 4.7%, with sector deviations mainly in energy and utilities. Exclusions increase exposure to profitability while slightly reducing investment and value factors. An optimised reallocation materially reduces tracking error and factor deviations, making it preferable for investors subject to fiduciary responsibilities per Plagge (2023). While naïve reallocation systematically lowers carbon footprints, optimised reallocation has no significant impact on carbon footprint reduction.

Exclusions based on consensus or net-zero criteria can have limited impact on financial risk, which can be further reduced with optimised reallocation. However, reducing carbon footprints require additional constraints to avoid unintended effects. Future research could explore the impact of sustainability measures beyond exclusions, such as reducing emissions or financing solutions aligned with sustainable development goals, on index risk profiles.

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Mitigating tail risks without sacrifice: empirical evidence of risk-based diversification benefits for equity investors

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Benoit Vaucher, Head of Research, Scientific Portfolio

Key takeaways

Diversification, especially when based on risk contributions, reduces the likelihood of extreme losses, making it a practical tool for risk management.[1]

The marginal benefits of diversification are diminishing: adding more diversification to an already diversified portfolio does not significantly improve extreme risks.

Diversification benefits can be achieved while maintaining the level of active risk[2], an important feature for investors seeking to both fully utilise their active risk budget and manage extreme losses.

Risk-based diversification is achievable without reducing expected long-term returns.

Introduction

The benefits of diversification for managing risk have been known since the 18th century (Bernoulli [1738]). At its core, diversification is a risk mitigation mechanism consisting in spreading capital across different investments to avoid the co-occurrence of losses. In equity portfolios, there are essentially two approaches to diversification. The first relies on the distribution of weights, either at the stock or sector level (eg, (Kacperczyk, Sialm and Zheng [2005], Brands, Brown and Gallagher [2005]). The second focuses on the diversification of risks (eg, Meucci [2009]).

Despite its theoretical appeal for portfolio construction (Asness, Frazzini and Pedersen [2012], Bhansali et al [2012]), the impact of risk-based diversification on portfolio performance and extreme risk remains underexplored. This gap arises partly because the concepts of diversification and risk are often amalgamated due to the role that correlation plays in connecting both notions. However, risk and diversification are not the same: portfolios with similar risk levels can exhibit different levels of diversification, influencing performance and vulnerability to extreme losses.

We address this gap by analysing how holdings-based and risk-based active diversification (ie, in excess of a benchmark) affect equity portfolios in terms of active risk and extreme risk, as measured by the expected shortfall (CVaR), and performance expectations. Beyond providing an accurate empirical analysis using a large sample of US equity funds, we employ a novel approach based on the generation of portfolios with identical risk levels, so-called iso-risk portfolios, to isolate diversification effects while controlling for risk and holdings concentration. This approach allows deeper insights than would normally be possible using the available empirical sample alone.

Our research highlights the following three key points:

- ***Empirical analysis:*** We find that active[3] funds – defined as funds materially deviating from the market cap-weighted benchmark – concentrate risks in a few factors, typically size and value, and that extreme risk (95% CVaR) is mitigated when increasing diversification of risks or sector holdings but is not impacted by the level of exposure-based or stock-level concentration. These effects are robust to alternative definitions of extreme risk, such as maximum drawdown. We also find decreasing marginal effects: while diversifying a portfolio's risk can reduce by as much as 20% the probability of having a large CVaR for concentrated funds, the effect plateaus and is negligible for already well-diversified funds. Hence, investors do not need to fully maximise diversification to reap its full benefits in terms of reduction of bad performance surprises.
- ***Iso-risk portfolios:*** Our unique dataset of iso-risk portfolios demonstrates that risk-based diversification allows a risk budget to be managed efficiently: its benefits can be achieved regardless of the

1 For the original unabridged version of this paper, see: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5095454

2 Also known as tracking error and defined as the standard deviation of returns relative to a given benchmark.

3 We focus on *active* portfolios; hence the discussion involves active diversification and risk measures.

starting risk level, suggesting that investors can diversify without necessarily reducing their target active risk. While controlling for the effect of risk and holdings concentration, we find that risk-based diversification has stronger mitigating effects than sector-based measures. The marginal impact depends on current diversification levels, not risk levels.

- ***Performance impact:*** Diversification, whether risk- or sector-based, does not significantly affect long-term expected returns. This result, combined with the previous insight, ie, additional diversification does not require the risk level to change, makes diversification a powerful and complementary tool for active managers with discretionary views on future returns.

Data and methodology

We begin with a cross-sectional analysis of 476 US equity mutual funds from the Morningstar database, covering January 2019 to December 2023. These funds collectively invest in over 1,900 individual stocks, offering a wide variety of risk profiles and compositions. To further enhance the analysis, in a second step we generate 39,400 randomised portfolios using the iso-risk methodology described later starting from daily return data. Funds included in the sample are active, meaning they meaningfully depart from the benchmark (minimum tracking error of 2%), and have a model R^2 of at least 0.80, to guarantee reliability of the statistics derived from the risk model.

Risk factor exposures and extreme risk

Risk-based diversification relies on a risk model. We employ the (Fama and French [2015]) five-factor model (market excess return, size, value, profitability and investment) plus the momentum from Carhart (1997) and the betting against beta factor (BAB) from Frazzini and Pedersen (2014), henceforth referred to as volatility.[4] Factor loadings are estimated using five years of historical data (January 2019–December 2023), and the market factor serves as the benchmark for active returns and risks.

Active extreme risk is measured as the 95% active conditional value-at-risk (CVaR) based on daily returns. To maintain consistency across instruments, we use model-implied returns and apply the Cornish-Fisher expansion methodology from Mark and Vaucher (2023), which provides more robust and reliable estimates compared to historical CVaR (Pritsker [2006]). Instrument betas and extreme risk estimates are calculated using daily data from the same five-year period. Robustness tests show that results remain unchanged extending the estimation window to 20 years.

Diversification measures

Portfolio theory often considers a portfolio well diversified if it achieves the highest reward per unit of risk. However, since expected returns are difficult to estimate (Merton [1980]), portfolio managers prefer to focus on more heuristic definitions that capture the idea of spreading risk across different assets (Martellini and Milhau [2018]). In line with this approach, the analysis employs four diversification measures: two based on holdings and two on risk.

- ***Holding-based diversification:*** One of the most classical concentration measures is the concentration of weights. It is measured using the Herfindahl–Hirschman index (HHI), which corresponds to the sum of squared portfolio weights using either stock-level and sector-level holdings (eg, Brands, Brown and Gallagher 2005). When employed to assess active diversification, weight concentration becomes cumbersome to interpret for small active weights. To address this issue, we define the active holding diversification (AHD) and active sector diversification (ASD) as the inverse active HHI (with active stock and sector weights, respectively) normalised by the squared sum of their active capital, as explained in Bagnara and Vaucher (2024).
- ***Risk-based diversification*** is measured using active factor diversification (AFD) and active risk diversification (ARD). AFD is a concentration measure that uses active risk exposures (betas) instead of weights. On the other hand, the ARD uses active risk factor contributions summing to the portfolio's active risk (Bagnara and Vaucher [2024]). Portfolios with well-distributed exposures across risk drivers exhibit higher AFD, with $AFD = 7$ indicating maximum factor diversification (equal exposure across all seven factors). Analogously, ARD reaches its maximum of 7, when total active risk is evenly distributed among risk factors.[5] ARD captures the effective number of active bets, where diversification is evaluated in terms of risk contributions rather than just exposures.

In the last part of the analysis, we use the factor intensity (FI), which represents total active exposure to risk factors relative to the market. FI is proportional to the funds' performance expectations, when assuming that in the long run the risk premium of all factors is the same, as we explain later.

Iso-risk portfolio rotations

Statistical studies on the relationship between portfolio characteristics and diversification often face limitations due to small sample sizes. Traditional methods like conditional double sorts, eg, on diversification and extreme risk, become impractical when empirical data is limited.

To overcome this, we use the iso-risk portfolio rotation method, which generates a large number of alternative portfolios with identical active risk and weight concentration as existing stock portfolios. This approach allows us to significantly expand the sample and analyse the relationship between diversification and performance for any given level of risk. For a detailed explanation of this technique and its implementation, we refer interested readers to Vaucher and Bagnara (2024b).

Long-term performance

Imposing diversification on an otherwise unconstrained portfolio may give rise to a cost in terms of performance, as it may force the active portfolio manager to reallocate capital from stocks where she has an informational advantage to a broader set of investments. In other words, increasing diversification reduces the transfer coefficient and with this also the expected value added by active management. Estimating this cost empirically is challenging, as it requires a number of assumptions about investors' priors and beliefs.

Our expanded portfolio sample with controlled risk levels offers a unique opportunity to examine the relationship between diversification and performance. Unlike much of the existing literature, our approach does not rely on historical performance. Instead, we simply assume that over the long term, all risk premia are expected to converge to the same value. Under this assumption, which provides an agnostic perspective on factor rewards, and no arbitrage, the long-term expected return of an asset in a linear factor model is its factor intensity FI scaled by the expected risk premium. Consequently, we focus on the cross-sectional variation in

4 We thank AQR Capital Management for BAB data (https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly) and Kenneth French for the other risk factors (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

5 An alternative measure of risk-based diversification it the effective number of bets, or ENB (Meucci [2009], Martellini and Milhau [2018]).

FI to explore the relationship between diversification and long-term performance, independently of the historical sample.[6] This agnostic approach is particularly valuable, as previous studies on risk-based diversification and performance often yield sample-dependent results (Chaves et al [2011]).

Results

Stylised facts about diversification

Figure 1 presents descriptive statistics for the diversification measures, along with active annualised risk (TE) and active daily 95% CVaR, which assesses tail risk at the daily frequency. CVaR, referred to as extreme risk, is always measured relative to the benchmark and in absolute values, with higher levels indicating greater potential losses.

The median ARD is 2.04, indicating that most funds spread active risk across only two factors. Only about 20% achieve ARD above 3. The median AFD is even lower at 1, with just 10% of funds diversifying across more than two factors. These findings reflect the under-diversification documented in Uppal and Wang (2003) and Han et al (2024). Holdings-based measures (AHD, ASD) show less skewed distributions, with the average fund actively investing in 117 stocks and about five sectors.

To identify in which few factors funds are mostly concentrated, we compare the top and bottom 20% of funds for each measure. ARD- and ASD-concentrated funds have higher exposures to size (average about 0.45 and 0.25) and value (about 0.1 for both) compared to the most diversified group, which shows near-zero exposures on average. In contrast, funds ranked by AFD and AHD display higher exposures to size and value as diversification increases.

1. Diversification measures: descriptives

	ARD	AFD	AHD	ASD	TE (%)	CVaR (%)
N	476	476	476	476	476	476
mean	2.28	1.09	116.68	4.52	7.05	1.03
std	0.89	0.76	43.37	1.07	3.19	0.46
min	0.83	0	20.97	3.12	2	0.28
1%	0.98	0.01	30.3	3.16	2.08	0.31
5%	1.17	0.05	54.59	3.38	2.41	0.36
10%	1.32	0.12	65.59	3.46	3.01	0.46
25%	1.64	0.4	85.5	3.74	4.73	0.71
50%	2.04	1	110.4	4.13	6.61	0.97
75%	2.85	1.73	142.74	5.06	9.17	1.33
90%	3.62	2.11	188	6.32	11.72	1.69
95%	3.95	2.29	196.66	6.67	12.88	1.85
99%	4.65	2.86	209.57	7.55	14.49	2.08
max	5.02	3.27	218.47	7.8	15.63	2.25

Descriptive statistics for active risk diversification (ARD), active factor diversification (AFD), (normalised) active holding diversification (AHD) and (normalised) active sector diversification (ASD), active annualised risk (TE) and active daily CVaR in %. US funds, 2019-23.

2. Multivariate analysis

	CVaR I	CVaR II	CVaR III	CVaR IV	CVaR V
Intercept	0	0	0	0	0
	-0.041	-0.041	-0.043	-0.042	-0.036
ARD	-0.447*				-0.214*
	-0.041				-0.043
AFD		0.446*			0.303*
		-0.041			-0.038
AHD			0.367*		0.227*
			-0.043		-0.038
ASD				-0.415*	-0.192*
				-0.042	-0.042
R^2 Adj.	0.198	0.197	0.133	0.171	0.389
N	476	476	476	476	476

Multivariate analysis described in (1). Stars (*) indicate statistical significance at the 10% level. Data is standardised.

Diversification and extreme risk

As a risk-mitigating tool, diversification aims to reduce large losses. To test this hypothesis, we regress CVaR on various diversification measures according to the following specifications, using standardised data for comparability:

$$
\begin{aligned}
CVaR_i &= \alpha + \beta_1 ARD_i + \varepsilon_i \\
CVaR_i &= \alpha + \beta_1 AFD_i + \varepsilon_i \\
CVaR_i &= \alpha + \beta_1 AHD_i + \varepsilon_i \\
CVaR_i &= \alpha + \beta_1 ASD_i + \varepsilon_i \\
CVaR_i &= \alpha + \beta_1 ARD_i + \beta_2 AFD_i + \beta_3 AHD_i + \beta_4 ASD_i + \varepsilon_i
\end{aligned} \tag{1}
$$

Comparing several specifications with each other allows us to verify the stability of the association between variables controlling for other diversification metrics. Results are reported in figure 2.

ARD strongly reduces tail risk: an increase of one standard deviation (0.89) leads to a reduction of 0.45 standard deviations of CVaR.[7] Notably, ARD alone explains about 20% of the variation in CVaR, highlighting the strong relationship between extreme risk and diversification. Sector-based diversification has a similar effect, with a coefficient of -0.42. Other measures of diversification, on the other hand, have a positive and significant coefficient, meaning that they may even induce an increase in extreme risk, which means that diversifying weights or betas does not necessarily lead to a diversification of risks.

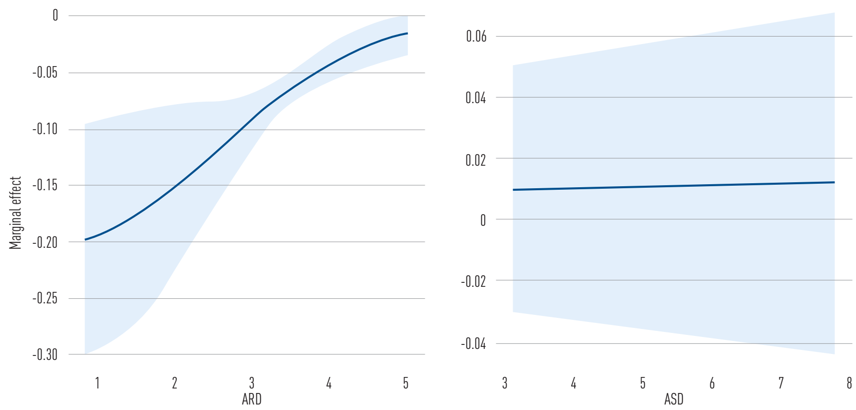
Non-linear marginal effects

The previous section established a positive linear relationship between diversification and the reduction of extreme risk. However, economic intuition suggests the relationship may not be entirely linear. To explore this, we use Probit models that allow us to estimate the probability of a high level of losses for any given level of diversification. To do so we introduce a binary variable, *high_CVar*, which takes a value of 1 when

6 Alternatively, one can assume that in the long run risk factors share the same reward-to-risk ratio (Sharpe ratio – SR) instead of the same risk premia. In this case, the expected return of an asset equals this common SR times a weighted factor intensity, where weights are determined by the relation between the volatilities of risk factors. Results under this assumption that analyse the impact of diversification on SR instead of expected returns are practically unchanged, and are available upon request.

7 Herzog et al (2023) find that ARD helps stabilise active risk by reducing the standard deviation of tracking error. Since CVaR can be seen as a function of high-order moments such as kurtosis (eg, Mark and Vaucher [2023]), our results confirm and generalise what they previously documented.

3. Probit marginal effects for high CVaR



Probit marginal effects for ARD and ASD based on the last specification in (2). In each panel, variables different than that represented on the x-axis are kept fixed at their mean. Shaded areas denote confidence intervals.

CVaR exceeds the 75th percentile and zero otherwise, and define its probability using the following models:

$$
\begin{aligned}
&Prob(high\_CVaR=1)=\phi(\alpha+\beta_1 ARD_i)\\
&Prob(high\_CVaR=1)=\phi(\alpha+\beta_1 ASD_i)\\
&Prob(high\_CVaR=1)=\phi(\alpha+\beta_1 ARD_i+\beta_2 ASD_i+\beta_3 AFD_i+\beta_4 AHD_i)
\end{aligned} \tag{2}
$$

where $\phi(.)$ is the standard normal cumulative distribution function.

We find that both ARD and ASD's mitigating effects on extreme losses persist and are strongly significant when considered alone, but, importantly, the effect of ASD is not significant anymore once we control for risk diversification. Non-linear models like Probit measure diversification effects depending on the diversification levels, instead of forcing linearity and thus assuming the same effect across the entire cross-section. This refined analysis reveals that only ARD systematically reduces the probability of incurring large extreme losses, while ASD does not.

This idea is better conveyed through the Probit marginal effects, which quantify the reduction in the probability of high CVaR in classical probability terms (Greene [2012]), depending on the starting diversification level. We plot such marginal effects in figure 3, where variables are displayed in their original scale.

ARD has a strong nonlinear impact. When ARD is low, improving it by one point diminishes the probability of large tail risk by 20%; at the median ARD (2.04), the probability decreases by 15%; for high ARD levels, a similar change reduces the chance by only 2%.

Thus, diversifying reduces extreme losses, but with diminishing marginal effects: while a good level of risk diversification is desirable, maximising diversification may not significantly improve risks beyond certain levels. Conversely, ASD (right panel) shows no significant impact after accounting for ARD. This shows that while improving ARD effectively lowers the likelihood of extreme losses, other diversification metrics, including ASD, provide limited additional benefit when ARD does not change accordingly.

Robustness tests: long-term CVaR and maximum drawdown

We conduct two robustness tests to validate the stability of our findings.[8]

- ***Longer-horizon active extreme risk.*** We extended the analysis to a 20-year period (2004–23) using model-implied returns based on each fund's betas and risk factor returns, which have longer data histories.[9] Calculating the 95% CVaR for this period, we repeat the linear regressions and Probit models. Results remain consistent even when computed on longer periods: ARD and ASD significantly impact CVaR in linear models (coefficients are -0.26 and -0.15, respectively), and Probit models confirm ARD as the sole metric robustly associated with reduced active tail risk.
- ***Alternative extreme risk measure: maximum drawdown (MDD).*** While CVaR is widely accepted and often used for regulatory purposes, another dimension of extreme risk is captured by the maximum drawdown (MDD), which is the maximum cumulative loss a portfolio experiences before reverting back to its value over a certain period. We estimated the maximum drawdown using model returns from the period 2019–23 and use it as independent variable in the previous models. Regression results align with those for CVaR: higher ARD and ASD levels correspond to lower MDD (coefficients are -0.17 and -0.09), though ASD's significance weakens when all metrics are included. Probit results again highlight ARD's prominent role in reducing the probability of high extreme losses, confirming the robustness of its mitigating capabilities across risk definitions.

Iso-risk analysis

Analysing the link between tail risk and risk-based diversification is challenging due to the intertwined nature of risk and extreme risk. Traditional statistical techniques require sample sizes that are currently not available, which makes it difficult to examine extreme risk while controlling for risk.

To address this, we develop a technique called iso-risk rotations that generates random portfolios with fixed risk and varying diversification levels.[10] Simply put, these transformations take an existing portfolio to produce a new portfolio with random weights but precisely the same level of risk and holdings concentration. With this technique, we can generate an unprecedented sample of portfolios with fixed levels of risk but different levels of diversification.

Selecting 197 funds with different risk levels from the empirical sample, we perform 200 iso-risk rotations on each fund to obtain 39,400 synthetic portfolios across 197 controlled levels of risk – an unprecedented dataset for our analysis. In this expanded sample, diversification metrics exhibit much greater variation than in the empirical data: ARD ranges from 0.8 to 6.1, ASD from 2.58 to 9.47, and AFD reaches almost 4. Meanwhile, active risk and CVaR distributions remain similar to the empirical sample. This approach is therefore able to generate synthetic portfolios with diverse diversification characteristics, allowing for a more precise assessment of diversification effects on extreme risk.

Diversification vs CVaR controlling risk levels

The iso-risk rotation approach allows us to analyse the relationship between diversification and CVaR while holding active risk constant. To achieve this, the generated portfolios are grouped into 49

8 Full tabulated results are available upon request..

9 Vaucher and Bagnara (2024a) demonstrate the validity of this approach when model fit is adequate. Our sample satisfies this criterion since selected funds have an R^2 of at least 0.80.

10 Iso-risk rotations maintain non-active holdings-based concentration constant, but not AHD.

equally spaced active risk intervals. Here active risk variations are limited to only 20–30 bps within each group, whereas diversification metrics vary more considerably.[11] Within each group, we run the previous regressions models:

$$\begin{aligned} CVaR_{i,j} &= \alpha_j + \beta_1 ARD_{i,j} + \varepsilon_{i,j} \\ CVaR_{i,j} &= \alpha_j + \beta_1 ASD_{i,j} + \varepsilon_{i,j} \\ CVaR_{i,j} &= \alpha_j + \beta_1 ARD_{i,j} + \beta_2 AFD_{i,j} + \beta_3 AHD_{i,j} + \beta_4 ASD_{i,j} + \varepsilon_{i,j} \end{aligned} \tag{3}$$

where $j = 1,\ldots,49$ denotes the risk group and $i = 1,\ldots, N_j$ denotes each portfolio belonging to the risk group j. Within each risk group, variables are standardised. The first two models assess the individual effects of ARD and ASD on CVaR, while the third controls for all diversification metrics, thus identifying their independent impact, at the same time leaving the active risk unchanged. Figure 4 visualises the coefficients of ARD and ASD from the third model across active risk levels.

Two key observations emerge. First, both risk-based and sector-based diversification reduce CVaR across all risk levels: the average coefficients for ARD and ASD are very similar when taken individually (-0.24 and -0.28), but ARD is more effective than ASD at mitigating extreme losses when controlling for all metrics (coefficients are -0.20 and -0.09, respectively) whatever the risk level. In other terms, risk diversification reduces extreme losses. Importantly, these benefits of diversification are observable and achievable at every active risk level: there are no clear regions where coefficients are systematically positive for ARD or ASD in the figure. The fact that increasing diversification does not require day-to-day risk to be reduced systematically is particularly appealing for investors adhering to strict risk budgets and wanting to fully consume their budget while mitigating extreme risks. We find similar results with alternative calculations of active risk groups.

Expected performance

We conclude by addressing the impact of diversification on expected performance. As we have explained before, we use the portfolios' active factor intensity (FI) as a robust estimate of long-term expected returns. Because risk has an important impact on performance, we used our enlarged sample, and thus we can investigate the relationship between robust long-term returns and diversification while neutralising the effect of risk. To do so, we used the same 49 active risk groups obtained with iso-risk portfolios and estimated the relationship between diversification using the models specified in (3) with FI as the left-hand side variable. Figure 5 shows the coefficients for ARD and ASD resulting from this exercise across the risk groups.

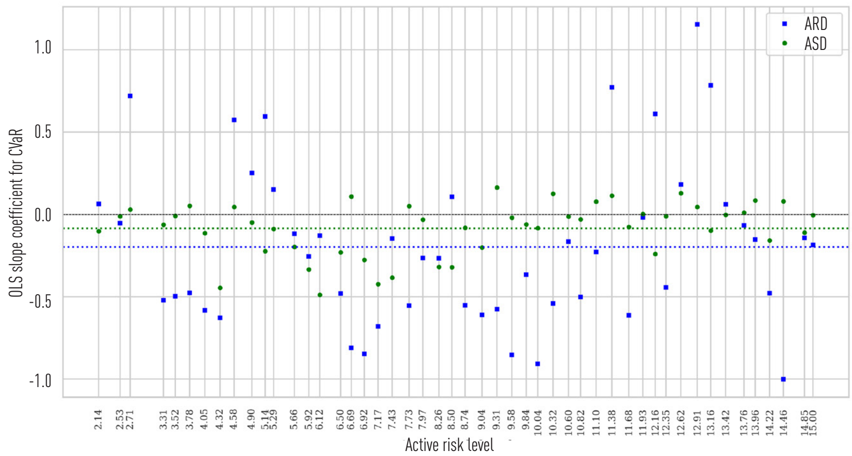
The average coefficients for ARD and ASD are generally small and statistically insignificant, suggesting no material relationship between diversification and expected returns. This shows that at every active risk level, more diversification is not linked to a reduction in expected performance.[12] In practical terms, this also means that adding diversification does not require the active risk level to be changed to maintain long-term expected returns.

Conclusion

The key takeaways for investors resulting from our analysis are the following:

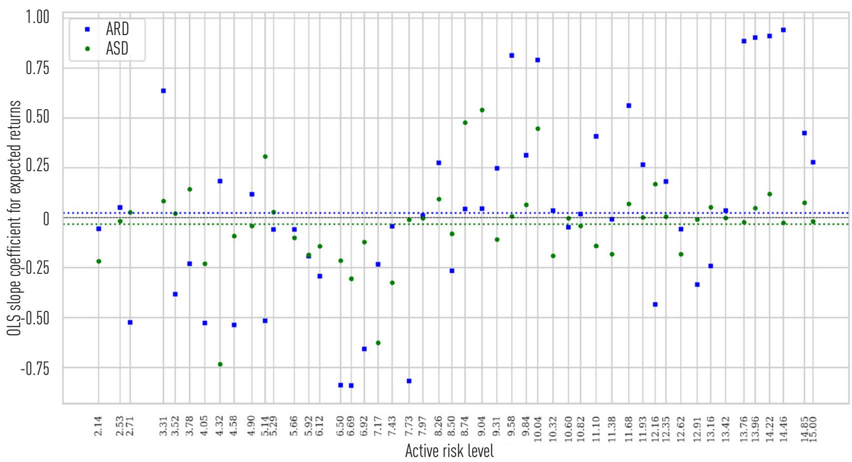
- ***Benefits of risk-based diversification.*** Diversification reduces the likelihood of extreme losses but in practice managing extreme risk is more effective with risk-based diversification than traditional holdings-based measures, including sector-based diversification, as its effect is robust to a variety of statistical tests.
- ***Diminishing marginal benefits.*** Adding

4. Impact of diversification on CVaR controlling for active risk level



Regression coefficients of ARD and ASD according to the last specification in (3) across all 49 active risk groups. Dotted lines represent the average coefficients.

5. Impact of diversification on expected returns controlling for active risk level



Regression coefficients of ARD and ASD according to the last specification in (3) across all 49 active risk groups. Dotted lines represent the average coefficients.

11 Notably, we find that the range of achievable diversification narrows as active risk increases: for example, ARD can vary by up to 2 units for low-risk funds (2% active risk) but by less than 1 unit for high-risk funds (15% active risk).

12 Since the risk groups are built so that the active risk is kept approximately constant, the average SR per group is proportional to the average FI up to a constant. Hence, the results shown here hold also for portfolio SR and not only for expected performance. Results available upon request.

more diversification to an already diversified portfolio does not significantly improve extreme risks. Being "diversified enough" is sufficient.

- ***Effective risk mitigation.*** Diversification reduces extreme losses across risk levels and can be achieved without having to underutilise a target day-to-day risk budget. For structurally higher-risk portfolios, diversification is a good substitute for de-risking.
- ***Minimal impact on performance.*** Adding diversification has no significant effect on expected performance. This is an important feature for active managers who wish to reflect their discretionary views on future returns in the allocation process.
- ***Bottom line:*** Risk-based diversification is a powerful, reliable tool for investors looking to reduce extreme risk and enhance portfolio resilience without underutilising their risk budget or compromising performance.

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