The Green Edge: Carbon Profitability Divestments

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Abstract

Passive investors need benchmark-disciplined methods to cut financed emissions without placing unintended bets. This paper applies Relative Carbon Profitability (RCP) as a cross-sectional signal of carbon efficiency, ranking firms by the value of cash generated per unit of Scope 1 + 2 emissions relative to industry norms. By incorporating the RCP ranking as an exclusion signal within benchmark-tracking equity portfolios, we integrate this information directly into the portfolio-construction process. Based on quarterly MSCI All Country World Index constituents from 2009 to 2024, we evaluate the risk-adjusted performance of two reinvestment strategies, pure exclusion and best-in-class, focusing on carbon footprint, factor exposures, and tracking error. Both strategies produce substantial reductions in financed emissions while preserving portfolio riskreturn characteristics close to the benchmark. Performance attribution analysis suggests that any excess returns are largely explained by stock selection within sectors rather than shifts in sector or regional tilts. In contrast, carbon intensity screens based on emissions per unit of revenue reduce portfolio emissions mainly by excluding high-emitting sectors, which increases active risk. RCP-based portfolio selection achieves similar emissions reductions while maintaining diversification across transition-relevant sectors, improving the practical implementation for asset owners operating under explicit tracking-error budgets and governance limits.

Keywords: Sustainable Investing; Portfolio Decarbonization; Relative Carbon Profitability; Weighted-Average Carbon Intensity; Exclusion Screening; Tracking Error; Financed Emissions
JEL: G11, G12, G15, Q54, Q56

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1. Introduction

Climate change is a defining challenge with direct effects on the real economy and financial markets. Limiting global warming requires substantial reductions in greenhouse gas emissions, and this constraint increasingly shapes risk management, investment mandates, and valuation through both cash-flow and discount-rate channels (IPCC, 2023; Bolton et al., 2020). For many passive investors, an important consideration is how to design strategies that reduce financed emissions while preserving diversification and mandate consistency. Reducing a portfolio's financed emissions lowers exposure to carbon risk, although implications for expected and realized returns must be evaluated explicitly (Bolton and Kacperczyk, 2021).

Policy momentum after the Paris Agreement has increased the focus on transition pathways and portfolio alignment with net-zero objectives. Translating such ambitions into portfolio practice requires investors with benchmark mandates to navigate two trade-offs: (1) choosing between engagement and divestment as mechanisms of influence and (2) balancing benchmark discipline against higher tracking risk (Broccardo et al., 2022). Recent regulatory initiatives provide guidance by formalizing climate benchmarks that target staged emission reductions with controlled risk, notably the EU's Climate Transition Benchmark (CTB) and Paris-Aligned Benchmark (PAB) frameworks (EU, 2020). Within these frameworks, Bolton et al. (2022) demonstrate a feasible portfolio strategy that minimizes ex-ante tracking error under a 25% initial reduction in portfolio emissions followed by an 8% annual reduction, assuming firms maintain current emission levels.

Effective portfolio decarbonization is contingent on, and largely determined by, the choice of an appropriate emissions metric. Practice often relies on backward-looking intensity ratios, such as emissions per unit of revenue, which are standard in reporting frameworks and climate-benchmark regulation (EU, 2020). These measures are transparent and comparable but can induce sizable allocation tilts away from benchmark exposures that do not necessarily reflect meaningful within-portfolio emissions reductions (Hartzmark and Shue, 2023).

Building on Ang et al. (2024), this study applies Relative Carbon Profitability (RCP) to rank firms by value generated per unit of carbon within their industry, and this ranking forms the basis for exclusion and reinvestment strategies. The metric is simple to implement in portfolio construction and complements intensity-based metrics by favouring firms that achieve both lower emissions and higher operating efficiency. This perspective is consistent with prior research showing that efficiency-based signals link environmental measures to operating productivity and profitability (Garvey et al., 2018). Since RCP ranks firms within sectors, the resulting portfolios tend to remain close to benchmark sector and regional compositions while reallocating toward more carbon-efficient firms.

Academic interest in the link between environmental and financial performance predates the carbon risk debate by several decades. Early studies, such as Spicer (1978) and Shane and Spicer (1983), explore whether environmental performance is priced, and their findings provide support for the notion that pollution control correlates with higher

profitability and lower risk. In a similar vein, Chava (2014) finds that a firm's environmental performance is an important determinant of its financing costs; firms with poorer environmental practices face higher expected returns on equity and higher borrowing costs, implying that markets price environmental risk as a component of overall firm risk. Building on the "Porter Hypothesis", Porter and van der Linde (1995) reframed pollution as a symptom of resource waste, proposing that well-designed regulation can spur innovation and raise productivity. This idea seeded the natural resource-based view of the firm (Hart, 1995; Hart and Dowell, 2011), and subsequent studies documented positive or U-shaped relationships between carbon or energy efficiency and firm performance (Hart and Ahuja, 1996; Busch and Hoffmann, 2011; Trumpp and Guenther, 2017). In this view, higher resource utilization is seen as an ability that is valuable, rare, and hard to imitate, thereby improving competitiveness (Buysse and Verbeke, 2003). Carbon profitability builds on this logic by implying that firms producing more economic value per unit of emissions may sustain a competitive advantage. By replacing carbon intensity with RCP as the exclusion criterion, this study contributes to the growing body of literature on constructing climate-aligned portfolios without sacrificing diversification or financial performance (Jondeau et al., 2025; Bolton et al., 2022).

We evaluate two transparent rules-based portfolio strategies. The pure exclusion (PX) strategy removes the worst-ranked firms according to a threshold, and proportionally redistributes weights to the remaining constituents. The best-in-class (BIC) strategy reinvests in higher-ranked peers from the same sector and region for each excluded firm, thereby limiting unintended tilts by construction and aligning with climate-benchmark guidance (EU, 2020). The screening thresholds are set to retain firms accounting for the top 99%, 90%, and 75% of the benchmark's total market capitalization. Portfolios are rebalanced monthly with annual emissions updates and standard index changes, matching live, rules-based implementation. The characteristics of the RCP-based portfolios are compared against corresponding portfolios constructed using carbon intensity as the exclusion criterion to evaluate differences in emissions reductions, sources of active risk, and risk–return outcomes.

Our investment universe is defined as the MSCI All Country World Index (ACWI), covering the period 2009 - 2023. The PX strategy achieves sizable reductions in financed emissions while maintaining portfolio characteristics close to the benchmark. Active returns remain small across all thresholds, and tracking error increases gradually as exclusions tighten. This is mainly driven by allocation rather than selection effects. The BIC strategy maintains sector and regional neutrality by design, and delivers emission reductions similar to the PX strategy. Tracking error remains modest, and active returns are largely driven by stock selection within sectors rather than allocation shifts. We also find that the exclusion signal governs how decarbonization is achieved; carbon intensity screens tend to raise tracking error through allocation effects, whereas the RCP screen tends to generate more of the active return from stock selection.

The economic interpretation is clear. RCP evaluates firms on the intensive margin of value creation per unit of carbon, benchmarked against industry norms and adjusted for

firm size. A decomposition using forecasting regressions shows that the asset-turnover and profitability components of RCP are strong predictors of next year's operating cash flow relative to assets, whereas emissions-to-sales intensity loses significance once basic controls are applied. Acting on this margin reduces financed emissions while retaining productive capital, aligning decarbonization with economic performance. This approach addresses a key challenge in sustainable investing, namely how to balance climate alignment with investment efficiency. Our study tests whether portfolios screened on RCP better capture firms that combine low emissions with strong fundamentals. In doing so, it extends research on resource efficiency, green premia, and climate risk pricing, and informs the broader debate on aligning fiduciary duties with sustainability objectives.

Assuming RCP identifies firms that are comparatively more efficient at converting carbon inputs into economic output, it becomes important to assess whether portfolios structured around this signal maintain financial performance alongside meaningful emissions reductions. Portfolio returns depend on both expected and realized components. In equilibrium, if investors prefer greener assets, expected returns on green stocks can be lower (Pástor et al., 2022; Pedersen et al., 2021; Hong and Kacperczyk, 2009), and higher emissions have been associated with higher expected returns after controlling for standard factors, consistent with a carbon-risk premium (Bolton and Kacperczyk, 2021). Realized performance varies with climate-related news and valuation premia (Ardia et al., 2023; Pástor et al., 2022), and portfolio decarbonization can add selling pressure to high emitters with price effects that at times offset higher expected returns (Rohleder et al., 2022; Cheng et al., 2024). The results in this study appear broadly consistent with these findings and point to a complementary channel related to transition risk that can shape performance differences between the signals. Firms with higher RCP generate more value for each unit of carbon emitted, which suggests stronger margins within their emissions footprint. These firms may be better positioned to absorb carbon costs, invest in abatement technologies, and adjust to tightening climate policies without the same valuation pressure that often affects more carbon-intensive producers. This ability to adapt can help reduce downside transition exposure.

For institutional investors and asset allocators, the guidance is practical. To decarbonize a benchmarked equity allocation with minimal disruption, one should replicate the index in a way that respects the benchmark's sector–region structure, and prefer a signal that ranks within industries. RCP satisfies this criterion in the empirical analysis. Carbon intensity remains useful for reporting and disclosure, but under strict thresholds it embeds allocation effects that raise tracking error, which may spill over to realized returns. Görgen et al. (2021) show that carbon-measurement design choices materially shape factor exposures and the risk and return profile. Bruno et al. (2022) document that many ESG signals map into standard factors, implying that apparent performance often reflects factor loadings rather than pure alpha. A caveat is that simple screens can carry hidden costs and unintended tilts, so alternative measures and their factor correlations matter.

The remainder of the paper is organized as follows. Section 2 reviews the literature most closely related to our research. Section 3 describes the data, including summary statistics, index constituents, and underlying emissions data. Section 4 formalizes common portfolio carbon metrics, discusses their limitations, and introduces Relative Carbon Profitability as an alternative measure. This section further outlines the portfolio-construction methodology, including the exclusion rule and the reinvestment strategies. Section 6 presents empirical results on performance and attribution. Section 7 examines robustness across regions and compares RCP with carbon intensity as screening signals. Section 8 provides concluding remarks and identifies avenues for future research.

2. Literature Review

Surveys by the Network for Greening the Financial System (NGFS, 2019; 2020) show that, beyond the primary objective of maximizing risk-adjusted returns within mandate and risk limits, large institutional investors pursue two climate-related aims: (1) limiting reputational risk by avoiding assets that conflict with public climate commitments and (2) hedging portfolios from physical and transition risk. This pattern is consistent with findings in Krueger et al. (2020), who survey institutional investors and document a widespread belief that carbon risk is financially material. Such views imply a focus on strategies that protect portfolio value rather than target external climate outcomes. Bonnefon et al. (2025) use incentivized auction experiments to separate value alignment from impact seeking, and find that investors' willingness to pay rises approximately in proportion to the estimated size of firms' positive externalities, implying that value alignment dominates portfolio choice and impact concerns are limited.

Our study is relevant for investors seeking to protect portfolio value from climate-related risk and adds to the literature on low-carbon investment strategies. Building on the low-carbon index framework of Andersson, Bolton, and Samama (2016), Garvey et al. (2018) show that portfolios with lower carbon footprints tend to achieve higher risk-adjusted returns in global equity markets. Consistent with this finding, several studies show that "green" stocks have outperformed their more carbon-intensive counterparts (e.g., Albuquerque et al., 2020; Pástor et al., 2022). This pattern has proved durable; Bauer et al. (2022) and Bernardini et al. (2021) document that the relative outperformance of low-carbon portfolios has persisted over much of the past decade.

2.1. Approaches to Portfolio Decarbonization

Investors increasingly rely on four main decarbonization approaches to mitigate exposure: screening, best-in-class tilts, shareholder engagement, and thematic or impact allocations. Negative screening excludes sectors or issuers that breach predefined criteria. Traditional exclusions include alcohol, tobacco, and gambling (Hong and Kacperczyk, 2009), and have since expanded to cover high emitters by some. Heinkel et al. (2001) show that exclusion policies can raise the cost of capital for targeted firms, while Fabozzi

et al. (2008) and Bolton and Kacperczyk (2023) document return premia for carbon-intensive "sin" stocks. However, general-equilibrium models by Berk and van Binsbergen (2025) suggest that divestment alone has limited real-economy impact, as unconstrained investors often absorb the resulting trades and neutralize price effects. Cheng et al. (2024) argue that only a very large green investor base can produce persistent pricing shifts. In practice, portfolio managers complement these exclusion strategies with attention to diversification loss and benchmark neutrality, often relying on external exclusion lists developed by providers that follow international norms. Recent legislative pushback, such as Texas Government Code §809 restricting investment in funds that exclude energy companies, highlights the growing controversy surrounding exclusion-based investment strategies. The scale of formal commitments is large, with over USD 40 trillion recorded in the Global Fossil Fuel Divestment Database as of 1 May 2025.[1]

As an alternative or complement to exclusion, tilting strategies reallocate portfolio weights toward firms with stronger environmental performance rather than excluding heavy emitters. Best-in-class screens identify industry leaders (Amel-Zadeh and Serafeim, 2018), while simple tilts increase weights on firms with lower footprints or higher resource efficiency. From an asset-pricing perspective, sustained policy or preference shocks that raise the expected costs of carbon can depress the valuations of carbon-intensive assets and cash flows exposed to transition policies, creating long-run devaluation risk for brown holdings and a hedge motive for greener exposures (Engle et al., 2020, Allahdadi et al., 2024). Investor demand is consistent with such motives. The Morningstar globe-rating shock generated large reallocations toward high-sustainability funds and away from low-sustainability funds without accompanying outperformance, indicating revealed preferences or constraints rather than a performance chase (Hartzmark and Sussman, 2019). In practice, tilts preserve alignment with benchmark exposures, which helps explain their adoption by asset managers with market-neutral mandates.

Shareholder engagement represents a third strategy to pursue portfolio decarbonization, emphasizing active dialogue and proxy voting as a way of exercising "voice" in the classic framework of Hirschman (1972). This approach seeks to achieve environmental goals through influence rather than capital reallocation or "exit". The effectiveness of engagement is supported by empirical evidence, with studies documenting that dialogues and shareholder interventions can lead to measurable improvements in corporate behavior and performance (see e.g. Dimson et al., 2015; Appel et al., 2016; Dyck et al., 2019; Krueger et al., 2020; Naaraayanan et al., 2021). Although these findings highlight an important channel through which investors can influence firms, this body of research, together with work on thematic and impact investing (see e.g. Barber et al., 2021; Riedl and Smeets, 2017), falls outside the scope of this literature review.

A growing body of literature explores asset-pricing models that integrate environmen-

[1]The Global Fossil Fuel Divestment Commitments Database documents public fossil fuel divestment commitments made by institutions worldwide. It provides detailed information on the type of institution, geographic location, and the fossil fuel categories (coal, oil, and gas) covered by each commitment. See a complete overview and methodological definitions at https://divestmentdatabase.org/.

tal preferences and externalities into portfolio choice, yet the empirical case for carbon-tilted strategies remains uncertain. Notable contributions, such as Heinkel et al. (2001), Pástor et al. (2022), and Pedersen et al. (2021), show how screening and taste for green assets can move required returns and capital allocation, but the empirical findings on pricing are mixed. Some studies link emissions to higher expected returns, consistent with transition risk being priced, while others attribute realized outperformance of green assets to preference shocks rather than risk premia (Bolton and Kacperczyk, 2021; Pástor et al., 2022). This ambiguity motivates a careful separation of cash-flow channels from discount-rate effects when assessing carbon tilts. Transition risk - arising from policy, technology, and preference shifts (Semieniuk et al., 2021) - affect both cash flows and discount rates. Empirically, transition-risk exposures appear in risk premia, factor loadings, and in how markets react when climate concerns change (Engle et al., 2020; Ilhan et al., 2021; Hong et al., 2019). These channels affect asset prices when expected abatement costs rise for carbon-intensive firms and when investor demand for green holdings strengthens. Together, they explain why measured effects can alternate between repricing and risk compensation.

2.2. The carbon premium debate

Consistent with the notion of a priced transition risk, several studies report higher returns for carbon-intensive firms. Hsu et al. (2023) find that high-polluting firms tend to earn higher average returns, which suggests the presence of a risk premium. Monasterolo and De Angelis (2020) examine whether the Paris Agreement announcement altered the risk profile of carbon-intensive and low-carbon indices and find decreasing betas and higher portfolio weights for green indices, but little penalization of carbon-intensive assets. Along similar lines, Görgen et al. (2020) construct a Brown-Minus-Green factor that captures systematic variation in global equity returns. The factor improves model fit, yet its realized returns remain statistically insignificant, suggesting that carbon risk may not be associated with a persistent premium. Bolton and Kacperczyk (2021; 2023) show that absolute emissions predict higher returns, which they interpret as evidence of transition risk being priced. Other studies challenge that conclusion. Aswani et al. (2024) find that the premium weakens when emissions are scaled by sales or limited to disclosed values. Similarly, Görgen et al. (2021) argue that both green and brown stocks carry inherent risks but find no clear evidence of compensation for carbon risk in financial markets. This suggests that any potential return premium is neither robust nor systematically exploitable.

Irrespective of how emissions are measured, the studies above implicitly assume that realized returns approximate expected returns and thus capture the cost of capital. High realized returns could signal mispricing rather than risk compensation, which is an argument familiar from the broader ESG literature that links strong governance to subsequent outperformance (e.g., Gompers et al., 2003; Edmans, 2011; Lins et al., 2017). Edmans (2021) emphasizes that sustainability primarily affects expected cash flows rather than the cost of capital, implying that abnormal returns often reflect cash-flow news rather than changes in required returns.

One way to assess whether returns reflect mispricing or risk is to examine the behaviour of earnings surprises. La Porta et al. (1997) show that value stocks consistently exceed earnings expectations. In the ESG literature, Core et al. (2006) find no such pattern for well-governed firms, while Edmans (2011, 2012) and Fornell et al. (2016) document positive earnings surprises for firms with high employee or customer satisfaction. Atilgan et al. (2024) apply this approach to climate finance, showing that absolute emissions and changes in emissions are associated with positive surprises, whereas carbon-intensity measures are not. This suggests that any observed carbon premium may partly reflect outperformance rather than risk compensation. Taken together, these studies imply that markets may reward firms that convert resource inputs into economic outputs more efficiently.

2.3. Positioning of this Study and Contribution

This study builds on recent advances in climate finance by proposing an alternative screening methodology for portfolio decarbonization based on RCP. While prior work has examined exclusion policies, tilting, and benchmark-based optimization strategies, there is limited research on decarbonization approaches that rely on within-sector efficiency rankings and can be implemented without optimization or parametric risk models. We examine two rules-based strategies and evaluate how the choice of screening signal shapes the mechanism through which portfolios reduce financed emissions. This positions the analysis at the intersection of resource efficiency and enhanced index strategies, and our analysis demonstrates how different signals translate into selection versus allocation effects in passive equity portfolios.

3. Data and descriptive statistics

3.1. Index Constituents

The aim of our analysis is to replicate the MSCI All Country World Index (ACWI), a float-adjusted, market-capitalization-weighted benchmark covering 23 developed and 24 emerging markets. At each month-end from January 2009 through December 2024, we record the list of constituents and their free-float weights, merging MSCI security- and index-level data (firm identifiers, sector and country classifications, constituent weights, reported revenues, and the firm's share categorized as green revenues) with Refinitiv Datastream return and financial statement data (total return including dividends, total assets, and net operating cash flow). If a variable is missing on a given date, the observation is excluded from the cross-section of that month and the corresponding weights are redistributed. For all annual variables, gaps are forward-filled within the same fiscal year only to avoid incorporating stale information. As of 31 March 2025, the ACWI comprises 2,558 stocks with a combined free-float market capitalization of approx. USD 75.9 trillion. Individual company sizes range from USD 137 million to USD 3.34 trillion, and the ten largest firms together account for 20.5% of the total weight. This highlights the influence of mega-cap technology firms in global equity markets.

We assign each security to one of four regions: North America, Europe, Pacific, and Emerging Markets.[2] As of March 2025, the United States represents 64.6% of the ACWI market capitalization, followed by Emerging Markets at 21%. Within this segment, China alone represents 3.2%. The largest sector weights are Information Technology at 23.4% and Financials at 18.1%. We also perform the analysis for three of the sub-region indices, namely the MSCI Europe, Pacific, and North America.[3] This regional decomposition allows us to account for differences in sector composition, market depth, and local risk factors, thereby testing the robustness of our conclusions across different market environments.

To evaluate whether our findings merely capture recognized risk exposures, we analyze the portfolio's loadings on established factors. Specifically, we regress portfolio returns on the five Fama–French factors and Carhart's momentum factor.[4] We use region-specific factor sets for North America, Europe, and the Pacific, while global portfolios use the standard developed-market factors to ensure consistency across regions.

3.2. Carbon Emissions Data

At the most basic level, carbon emissions denote the aggregate mass of greenhouse gases (GHGs) released directly or indirectly by an activity. Under the Kyoto Protocol, volumes are expressed in carbon-dioxide equivalents (CO_2e) using 100-year global-warming potentials.[5] Corporate emissions are grouped into categories defined by the Greenhouse Gas Protocol. Scope 1 covers direct on-site emissions, Scope 2 covers indirect emissions from purchased energy, and Scope 3 covers all remaining upstream and downstream externalities along the value chain.[6] In the financial sector, financed emissions under Scope 3, Category 15 (Investments) represent the share of portfolio companies' or borrowers' emissions attributable to an investor's financing. Although financed emissions represent only one out of fifteen Scope 3 categories, they account for nearly all emissions attributable to asset owners and asset managers.

Measuring financed emissions is challenging. Estimation methods often rely on en-

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[2]MSCI's ACWI classification divides regions as follows: North America comprises the United States and Canada; EMEA (Europe, Middle East, and Africa) includes Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom; APAC covers Australia, Hong Kong, Japan, New Zealand, and Singapore. All remaining countries are classified as Emerging Markets.

[3]Within each MSCI regional index, sub-regions are defined as follows: Pacific comprises Japan, Asia ex Japan (Hong Kong, Singapore), and Oceania (Australia, New Zealand); Europe includes the Nordics (Denmark, Finland, Norway, Sweden), Western Europe (Austria, Belgium, France, Germany, Ireland, the Netherlands, Switzerland, United Kingdom), and Southern Europe (Italy, Portugal, Spain, Greece); North America includes the United States and Canada.

[4]Fama–French factor data are obtained from Kenneth R. French's online data library at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[5]The Kyoto Protocol regulates carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluoride; see UNFCCC (1998), Annex A.

[6]A schematic overview of these categories, including examples of upstream and downstream activities, is provided in Appendix B, Figure A1.

vironmental input-output models, borrower-level questionnaires, and industry-average emissions factors. These methods introduce inconsistency across data vendors, and create the potential for double counting. Regulators therefore tend to prioritize Scope 1 and Scope 2 disclosure, whereas Scope 3 estimates remain subject to phased implementation due to their reliance on model-based approximations and limited verification standards.

To obtain consistent coverage under these conditions, the study relies on MSCI ESG Research as its source of issuer level GHG emissions. The data are sourced primarily from the most recent corporate filings (annual and CSR reports, websites) and supplemented with Carbon Disclosure Project (CDP) and government databases when direct disclosure is unavailable. When firms do not report, MSCI applies proprietary estimation procedures for Scope 1 + 2 emissions separately, which allows partial disclosures to be incorporated into the analysis. A detailed overview of MSCI's estimation framework is provided in Appendix E, which also documents how reliance on the different estimation models evolves in our sample over time.

All annual emissions figures are winsorized at the 1st and 99th percentiles to limit the influence of extreme values, and absolute Scope 1 + 2 emissions are aggregated for every MSCI ACWI constituent between January 2009 and December 2023. The carbon dataset is updated once per year at the beginning of the third quarter. Specifically, in Q3 of year t, we load the latest available emissions data for fiscal year $t-1$. This reflects a realistic information set for investors: most firms release sustainability data between January and April alongside annual reports, and CDP submissions are due between July and September. As a result, a portfolio rebalanced in February of year t would not have access to the final emissions figures for year $t-1$. By keeping the values from the previous year for the whole trading year and only switching to the new vintage in Q3, our analysis reflects actual data availability and avoids trading on information that was not yet public. In an ideal setting, portfolio rebalancing would be perfectly aligned with each emissions data release, thereby eliminating look-ahead bias. Since this is not possible and MSCI discloses emissions annually, the dataset is updated once per year in Q3 with a one-year lag, and monthly observations are forward-filled until the next update.

We find that emissions remain relatively stable over time and that firm-level rankings change slowly, implying that the one-year lag in available data introduces minimal bias to portfolio-level estimates (see Appendix C for an overview). Since rank persistence is strong across both one- and three-year horizons, the difference between estimated and realized portfolio footprints tends to be modest, typically around one percent for broad benchmarks and slightly higher for low-carbon portfolios (Bixby et al. 2022). The limited discrepancies that remain mostly reflect differences in reporting calendars or retrospective data revisions, leaving only a small residual look-ahead bias.

To document the cross-sectional development of the emissions-data universe, Table 1 reports (i) the number of MSCI ACWI constituents, (ii) the share of firms with available Scope 1 + 2 data, and (iii) the share of total market capitalization covered for the ACWI, Developed Markets, and Emerging Markets from 2009 to 2023. Developed Markets are defined as the 23 advanced economies listed in the MSCI classification, while all

other economies fall into the Emerging Markets bucket. This breakdown highlights both improvements in disclosure over time and persistent gaps in lower-reporting regions.

Table 1: The number of firms (*Nb of Firms*), the proportion of firms covered (*% of Firms*), and the proportion of total market capitalization covered by Scope 1 + 2 emissions data (*% of Mkt Cap*) across three market segments: MSCI All Country World Index (ACWI), Developed Markets, and Emerging Markets. Developed Markets include the United States, Canada, Australia, Hong Kong, Japan, New Zealand, Singapore, Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Israel, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. All other economies not classified as developed are considered Emerging Markets, including those in Latin America, Africa, Eastern Europe, and parts of Asia. The data are reported annually from 2009 to 2023.

Year	**ACWI**			**Developed Markets**			**Emerging Markets**		
	Nb of Firms	% of Firms	% of Mkt Cap	Nb of Firms	% of Firms	% of Mkt Cap	Nb of Firms	% of Firms	% of Mkt Cap
2009	2642	54.54	69.62	1804	57.37	71.18	839	48.51	47.70
2010	2630	56.73	70.48	1755	60.06	72.18	875	50.06	49.51
2011	2633	59.48	71.23	1728	62.33	72.79	905	54.03	51.71
2012	2613	61.46	73.19	1718	64.14	74.62	895	56.31	54.26
2013	2608	63.80	74.86	1703	66.41	76.06	906	58.94	56.71
2014	2623	66.22	76.20	1722	68.18	77.09	901	62.49	61.77
2015	2697	67.63	78.81	1768	69.63	79.66	929	63.83	63.96
2016	2656	69.95	81.61	1769	72.58	82.67	887	64.71	63.34
2017	2659	73.34	83.90	1754	76.45	85.18	906	67.33	63.34
2018	2953	76.57	86.00	1731	79.38	87.37	1222	72.59	64.93
2019	3228	79.77	88.40	1745	82.92	89.88	1484	76.08	66.09
2020	3388	81.40	90.57	1782	84.85	92.11	1608	77.55	68.59
2021	3276	84.89	91.94	1678	87.37	93.02	1598	82.29	76.60
2022	3209	87.13	93.90	1634	89.84	94.51	1576	84.33	84.19
2023	3139	86.11	94.42	1582	90.58	94.89	1557	81.57	86.42

We observe a steady increase in both firm-count and market-capitalization emissions coverage, rising from roughly 55% of firms (70% of market cap) in 2009 to more than 85% of firms (94% of market cap) by 2023 for the ACWI. In all segments, market-capitalization coverage exceeds firm-count coverage, indicating that larger companies tend to disclose emissions data earlier than their smaller peers. Figure 1 further illustrates the improvement in corporate GHG reporting by breaking down the annual coverage of Scope 1 + 2 emissions for MSCI ACWI constituents into three parts: reported disclosures, model-based estimates, and missing observations. From 2010 onward, the share of reporting firms increased steadily from about 22% to over 70%, demonstrating growing coverage and transparency. The combined estimated and missing data series illustrate a decreasing reliance on proprietary imputation methods.

Accounting for Scope 3 emissions poses several methodological and practical challenges. Upstream and downstream data are often proprietary or highly aggregated, reporting boundaries and allocation rules vary across frameworks, and temporal mismatches arise when suppliers report for different fiscal years. Reliance on third-party estimates adds additional uncertainty, and even firms with advanced sustainability practices strug-

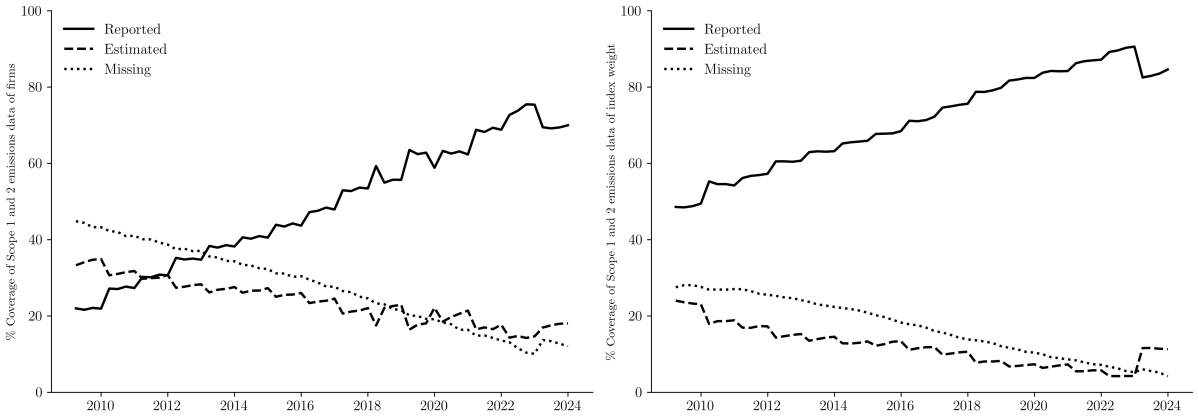


Figure 1: Annual coverage of Scope 1 + 2 emissions data for MSCI ACWI constituents, 2009–2023. Solid: reported; dashed: estimated; dotted: missing. Data sourced from MSCI ESG Research.

gle to produce complete, high-quality Scope 3 inventories. Among the ACWI constituents in our dataset, reported or estimated Scope 3 data were only available for approximately half of the firms by 2023. Although coverage has improved since 2009, disclosure quality remains uneven. We therefore focus on Scope 1 and 2, which benefit from broader coverage and more established external verification, to maintain consistency across firms, sectors, and time in a global sample. As data collection practices continue to develop and regulators move toward more standardized value-chain disclosure requirements, integrating Scope 3 will allow a more comprehensive assessment of climate risk.[7] Meanwhile, Scope 1 and 2 provide a transparent and comparable benchmark for assessing financed emissions in diversified equity portfolios over the full sample period.

4. Methodology

4.1. Portfolio Carbon Metrics

Ambitious net-zero pledges have limited operational impact unless investors can quantify the GHG exposure of their holdings and anticipate how this exposure shifts under alternative allocations. In practice, two complementary reporting standards now dominate carbon measurement of the portfolio. The Partnership for Carbon Accounting Financials (PCAF) is based on the Greenhouse Gas Protocol and focuses primarily on Scope 3, Category 15 investments. The Task Force on Climate-related Financial Disclosures (TCFD) provides a broader disclosure framework, which most regulators now follow.

[7]See Appendix B, Figures A2 and A3 for an illustration of how incorporating Scope 3 impacts the sectoral distribution of portfolio emissions.

Both PCAF and the TCFD group portfolio indicators into ownership-based metrics, which allocate a proportional share of absolute company emissions to each investor, and efficiency-based metrics, which assess how effectively firms generate economic or physical output per unit of carbon. These two perspectives complement each other: absolute emissions identify "hot spots," while intensity ratios show whether those emissions support productive activity. The choice of metric depends on the investor's objective. Weighted Average Carbon Intensity (WACI) is generally used to assess transition risk, Carbon Intensity (CI) aligns with fiduciary reporting objectives, and Carbon Footprint (CF) is suited for evaluating compliance with carbon-budget constraints. In practice, CF and CI represent the ownership-based category, whereas WACI captures the efficiency-based perspective.

4.1.1. Weighted-Average Carbon Intensity (WACI)

WACI is the indicator most commonly used in industry reports. At time t, the WACI for portfolio p is defined as

$$\mathrm{WACI}_t^p \;=\; \sum_{i=1}^{N_t} w_{i,t}^p \frac{E_{i,t}}{\mathrm{Rev}_{i,t}} \quad [\mathrm{tCO_2e}/\$\,\mathrm{m}], \tag{1}$$

where $w_{i,t}^p$ is the market-capitalization weight of issuer i, $E_{i,t}$ denotes the combined Scope 1 + 2 emissions, and $\mathrm{Rev}_{i,t}$ the revenue for the same reporting period. WACI measures tonnes per million dollars of output. The Task Force on Climate-related Financial Disclosures recommended WACI as its principal transition-risk metric in 2017 and has reaffirmed that recommendation in each guidance update since then. Subsequent revisions of the EU Sustainable Finance Disclosure Regulation and the ISSB's S2 standard adopt the same convention.

Unlike other metrics, WACI does not require market capitalization or enterprise value as inputs, which makes it applicable across a broad range of asset classes beyond equities and listed credit. The transparent formulation enables straightforward decomposition by sector, region, or factor and facilitates attribution analysis. However, since ownership shares are not incorporated, the metric reflects carbon efficiency rather than financed responsibility.

4.1.2. Carbon Emissions to Revenue Intensity (CI)

To account for ownership considerations, a financed version of WACI can be defined as

$$\mathrm{CI}_t^p \;=\; \frac{\sum_{i=1}^{N_t} o_{i,t}^p\, E_{i,t}}{\sum_{i=1}^{N_t} o_{i,t}^p\, \mathrm{Rev}_{i,t}}, \qquad o_{i,t}^p = \frac{V_{i,t}^p}{\mathrm{Cap}_{i,t}}, \tag{2}$$

where $o_{i,t}^p$ denotes the ownership share of issuer i, $V_{i,t}^p$ is the market value of the holding, and $\mathrm{Cap}_{i,t}$ is the issuer's total market cap. Portfolio weights are $w_{i,t}^p = V_{i,t}^p / V_t^p$, with $V_t^p = \sum_{i=1}^{N_t} V_{i,t}^p$ denoting the portfolio's total market value at time t. CI provides an

answer to the question "How many tonnes of emissions do we finance per USD million of revenue?" The PCAF describes economic emissions intensity (of which CI is the equity implementation) as a core metric for monitoring the decarbonization path of loan and investment books.

In contrast to WACI, CI scales both emissions and revenues according to ownership. For example, a ten-percent stake in a cement producer contributes only one-tenth of that firm's emissions and revenues to the portfolio total. This ownership adjustment makes CI particularly suitable for asset owners who regard financed externalities as part of their fiduciary boundary.

4.1.3. Carbon Footprint (CF)

The portfolio carbon footprint, defined as absolute financed emissions normalized by portfolio value, is given by

$$\mathrm{CF}_t^p \;=\; \frac{\sum_{i=1}^{N_t} o_{i,t}^p \, E_{i,t}}{V_t^p}. \tag{3}$$

CF quantifies the portion of global emissions effectively financed per dollar invested, such that each million allocated to the portfolio corresponds to CF_t^p tonnes of annual emissions. Although CF omits revenue adjustments, it remains a relevant measure for investors pursuing absolute decarbonization targets or operating under explicit limits on financed emissions.

4.1.4. Shortcomings of WACI, CI and CF

Reviewing these metrics highlights a clear disconnect between how emissions are measured and how firms generate economic value. By scaling emissions relative to sales, they may favor firms with higher margins even when these margins arise from pricing power rather than operational efficiency, creating a risk of conflating profitability with actual carbon productivity. Moreover, when both the numerator (ownership-adjusted emissions) and denominator (portfolio value) vary with market capitalization, a fund's carbon footprint can swing dramatically with general market movements. This can lead to fluctuations that mirror the revenue-driven cyclicality observed in WACI and CI, rather than reflecting decarbonization progress. Deciding on the denominator involves a clear trade-off: revenue normalization facilitates cross-sector comparison but adds volatility, whereas value normalization offers an intuitive carbon-budget metric at the cost of price sensitivity. Defining the purpose of portfolio carbon measurement beforehand prevents misinterpretation and reduces the risk of optimizing against inconsistent denominators.

Even when the purpose of carbon measurement is well defined, metrics such as WACI, CI, and CF remain largely backward-looking. They primarily address a compliance-oriented question of what the portfolio financed in the previous year, rather than informing forward-looking capital allocation. As a result, they offer limited guidance for identifying firms that are likely to create value in a world with tightening carbon constraints. These measures are also sensitive to procyclical noise and heightened volatility

when equity multiples compress, and therefore fail to provide the stable, forward-looking signal required for effective stock selection.

Moreover, normalizing by firm size conflates operational scale with efficiency. Suppose two utilities each emit one million tonnes of CO_2, but one generates USD 2 billion in revenue and the other USD 4 billion. An intensity ratio would assign the higher-revenue firm a lower carbon intensity, although its apparent edge may solely arise from pricing power rather than carbon efficiency. The equal, tonne-for-tonne burden both companies place on the global carbon budget is therefore overlooked. Asset allocators seeking to channel capital towards the efficient use of carbon require a metric that treats carbon explicitly as a scarce factor of production and measures incremental economic surplus per tonne emitted.

4.1.5. Relative Carbon Profitability

Ang et al. (2024) propose Carbon Profitability as a forward-looking signal of firm-level carbon efficiency. This measure assesses how much revenue a firm generates per unit of emissions relative to its industry average, and reframes decarbonization as a pursuit of carbon-efficiency leadership rather than a zero-emission objective. Instead of treating emissions as waste, it views emissions as a production factor and asks whether a firm's revenues exceed the expected level given its carbon footprint and sector norm. Firms that outperform this emissions-adjusted benchmark are seen as carbon efficient in economic terms, since they extract more value from each unit of carbon emitted.

The relevance of this perspective becomes clear when we examine sector-level averages for green revenues and carbon intensity. Table 2 shows that the sectors with the largest share of green revenues, such as Utilities and Industrials, are also among the most emission intensive. This pattern reflects the infrastructure-driven nature of the transition; building low-carbon systems like power grids or green buildings often requires emission-heavy inputs, even though the finished assets help reduce emissions over time.

Table 2: Sector-level averages for green revenues and Scope 1 + 2 intensity, based on data from January 2009 to December 2024. Green revenues represent the total of all revenues derived from any of the climate change environmental impact themes, including alternative energy, energy efficiency, or green building. Data sourced from MSCI ESG Research.

Sector	Nb. firms	Green Rev. (%)	S1+2 Intensity
Real Estate	200	23.56	88.12
Utilities	188	17.19	2,625.66
Industrials	715	11.52	200.02
Information Technology	545	9.59	73.53
Consumer Discretionary	534	6.11	67.19
Materials	429	5.11	1,171.40
Energy	168	2.67	586.60
Consumer Staples	320	2.19	90.57
Communication Services	204	1.15	50.48
Financials	745	0.58	28.02
Health Care	345	0.00	52.14
Telecommunication Services	72	—	62.92

This angle highlights how asset managers focusing solely on reducing carbon intensity may systematically underweight the very sectors central to climate solutions. Carbon Profitability addresses this mismatch by rewarding firms that generate high revenues per unit of emissions, regardless of sector, and offers an economically reasonable framework for supporting the transition while maintaining exposure to value generating assets.

Moreover, it is useful to examine the unconditional relation between firm size and emissions. Figure 2 plots firm revenues ($\log(\text{Sales}_{i,t})$) against carbon emissions ($\log(\text{CO}_{2,i,t})$) for all firms, colored by GICS sector. The cloud of points slopes upward, confirming that larger firms tend to emit more, yet at the same sales level firms vary greatly in how much CO_2 they emit. This dispersion is not just a sector effect, since sector colors are thoroughly mixed throughout the plot, and the vertical spread highlights substantial cross-sectional differences in value creation. Normalizing emissions by sales compresses this variation and obscures the distinction between operational efficiency and pricing power. Carbon Profitability overcomes this limitation by translating the scatter into a revenue surplus: given a firm's emission footprint and the benchmark implied by its industry, does it generate more or less output than expected?

Ang et al. (2024) formalize a sector-adjusted measure of carbon efficiency by constructing an industry-specific benchmark that reflects the average revenue generated per tonne of CO_2. Let $S_{i,t}$ denote firm i's gross revenues and $E_{i,t}$ its combined Scope 1 + 2 emissions in year t. To remove structural differences across industries, they define

$$\bar{\rho}_{j,t} = \frac{\sum_{k \in j(i)} S_{k,t}}{\sum_{k \in j(i)} E_{k,t}},$$

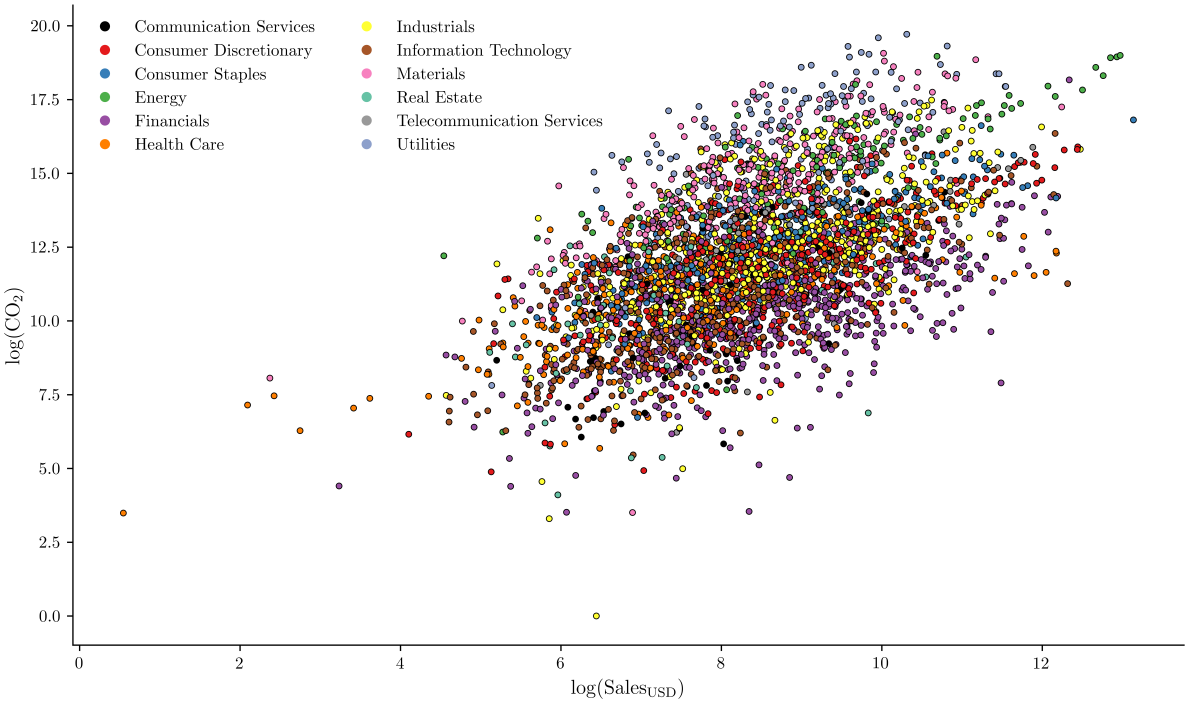


Figure 2: Scatterplot of log(Sales) vs. log(CO_2) by GICS sector. The vertical dispersion at a given emissions level indicates large cross-sectional differences in value creation. Universe is MSCI ACWI from 2009 to 2023. Each point is an ISIN averaged over years (arithmetic mean). Sales are in USD millions. Emissions are Scope 1 + 2 in metric tonnes CO_2. Emissions data sourced from MSCI ESG Research; sales from Refinitiv Datastream.

where $j(i)$ denotes the GICS industry of firm i. This ratio represents the industry-average revenue per tonne of CO_2 emitted. Building on this benchmark, the Carbon Profitability of firm i is defined as the residual surplus once its emissions are charged at the industry rate

$$\mathrm{CP}_{i,t} \;=\; S_{i,t} \;-\; E_{i,t}\,\bar{\rho}_{j,t}. \tag{4}$$

Equation (4) is intentionally simple. The first term, $S_{i,t}$, captures the firm's actual value creation, while the second term, $E_{i,t}\,\bar{\rho}_{j,t}$, represents the value it would have produced if it matched the industry-average carbon efficiency. A positive $\mathrm{CP}_{i,t}$ indicates that the firm generates more revenue per tonne of emissions than its peers, whereas a negative value signals relative underperformance.[8] To scale $\mathrm{CP}_{i,t}$ for firm size, Ang et al. (2024) divide by total assets $A_{i,t}$. This yields the Relative Carbon Profitability

$$\mathrm{RCP}_{i,t} \;=\; \frac{\mathrm{CP}_{i,t}}{A_{i,t}}, \tag{5}$$

[8]Expressing the surplus in dollars rather than as a ratio effectively assigns higher implicit charges to emissions in low-intensity sectors, where even small deviations from the norm carry greater informational content. Industry benchmarks are suitable because industry norms jointly shape emissions levels and their financial materiality, as codified in SASB standards.

which can be interpreted as the excess return on assets for firm i, after accounting for its emissions profile and industry benchmark. Together, Equations (4) and (5) treat carbon as a productive input and yield a metric that is neutral to both industry structure and firm size. These properties help mitigate the distortions that intensity ratios introduce into firm level comparisons. In line with Ang et al. (2024), we observe a cross-sectional rank correlation of 0.48 between RCP and the traditional revenue-to-emissions ratio after adjusting for industry effects, slightly below the 50% reported in their study. This confirms that RCP is more than a relabeled intensity measure; it produces a different ranking of firms.

Figure 3 compares the within-sector dispersion of RCP and carbon intensity across the eleven GICS industries. Each bar represents the cross-sectional standard deviation of the respective metric. The distribution of CI is highly uneven across sectors, with Utilities exhibiting a dispersion more than twice as large as that of any other sector. About half of all industries exhibit relatively narrow within-sector ranges. By contrast, RCP scales the role of emissions in low-intensity sectors and moderates the extreme effects in high-intensity sectors, yielding a flatter dispersion profile. In practice, tilting a portfolio toward RCP supports a sector-neutral allocation of capital while still distinguishing effectively among firms within each industry. Replacing an intensity-based tilt with an RCP tilt can therefore increase expected profit per tonne of CO_2, and capture the transition premium wherever it arises without introducing unintended sector tilts.

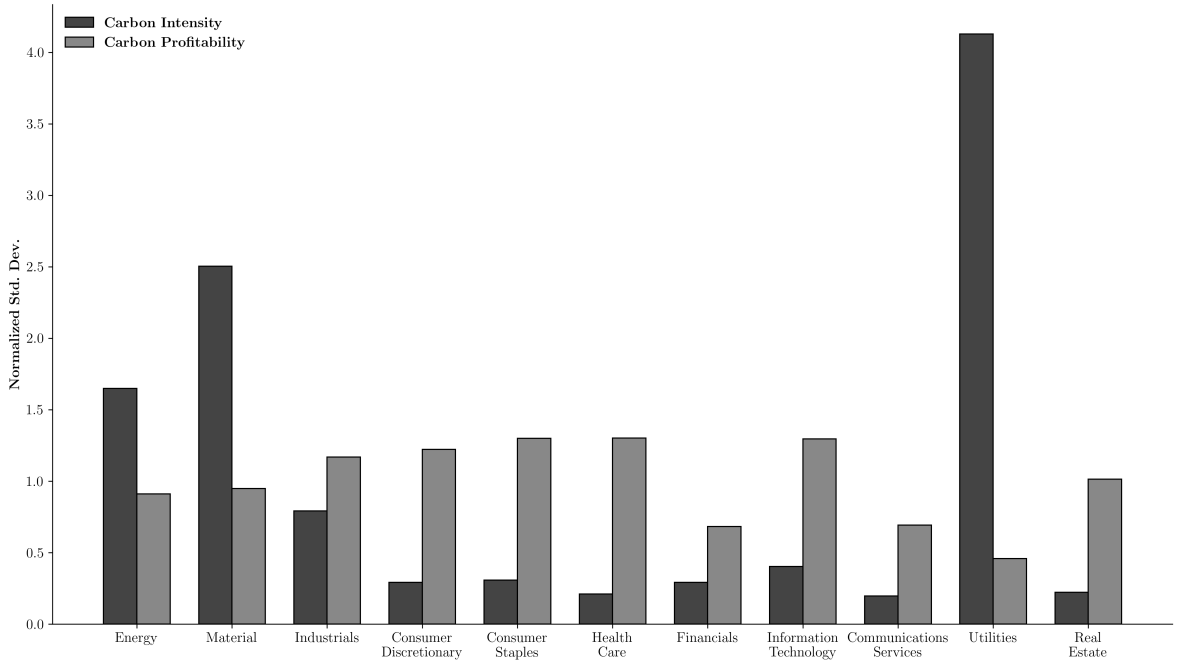


Figure 3: Bars report the normalized within-sector standard deviation of firm-level metric values in each GICS sector. We compute the cross-sectional standard deviation of firms within sectors for each year, average the annual dispersions across the sample period, and divide by the cross-sector mean such that 1.0 represents the sample-average dispersion. Values above 1 indicate greater-than-average dispersion, while values below 1 indicate less-than-average dispersion. Firm-level metrics are winsorized at the 1st and 99th percentiles before dispersion is computed. Averaged annual firm-year observations of MSCI ACWI constituents span from 2009 to 2023. Emissions data are sourced from MSCI ESG Research, and index constituents are from MSCI Inc.

To examine whether carbon profitability contains information about future operating performance, we follow Ang et al. (2024) and decompose $\mathrm{RCP}_{i,t}$ into terms that illustrate the economic channels through which carbon affects profitability:

$$\mathrm{RCP}_{i,t} = \underbrace{\frac{S_{i,t}}{A_{i,t}}}_{\text{asset turnover}} - \underbrace{\frac{E_{i,t}\,\bar{\rho}_t}{A_{i,t}}}_{\text{emissions-implied cost}} .$$

The first term captures operational efficiency, and the second term reflects the carbon-related charge for emitting, showing that carbon profitability equals the revenue generated per unit of assets minus the profit share that would be lost if emissions were priced at $\bar{\rho}_t$. This decomposition illustrates how firms with similar emissions levels can differ in performance: higher asset turnover increases carbon profitability, while greater reliance on emissions-intensive production reduces it. To assess whether these channels contain information about future operating performance, we examine next-year operating cash flow scaled by assets and regress it on lagged operating cash flow together with the carbon-based measures derived from RCP. The specification includes carbon profitability and its two components, along with the traditional emissions-intensity ratio for comparison. Our results are consistent with Ang et al. (2024): (1) the traditional emissions-intensity ratio is insignificant, indicating that emissions per unit of revenue offer little explanatory power once underlying profitability is controlled for, and (2) the operational-efficiency term is positive and significant, while the emissions-implied cost term is negative and significant, suggesting that firms generating revenue through more emissions-intensive processes tend to have weaker and less persistent cash-flow performance (see Appendix B, Table A1, for full results).

4.2. Exclusion Process

We examine how RCP functions as a screening signal by applying it to portfolios built around the market benchmark to evaluate the resulting trade-offs between emissions exposure and risk–return characteristics. The market-capitalization-weighted benchmark serves as the neutral reference. First, we create pure exclusion portfolios by removing firms with the lowest RCP values and redistributing their weights across the remaining constituents. Second, we form best-in-class portfolios by tilting the reallocated capital toward the highest RCP firms within each sector and region. Applying these procedures through time isolates the contribution of RCP screening to returns, risk, tracking error, and carbon exposure. Each portfolio is initialized with USD 10 million in assets under management. The results are evaluated against the benchmark across standard performance metrics, including tracking error and carbon reductions measured through WACI, carbon intensity, and carbon footprint, to quantify how RCP-based screening shifts the balance between decarbonization and financial performance.

Building on the portfolio framework of Jondeau et al. (2025), we replace the carbon intensity screen with an RCP-based ranking. Earlier studies, such as Andersson et al. (2016) and Bolton et al. (2022), show that ex-ante tracking-error minimization can lower

emissions while maintaining benchmark characteristics, but Jondeau et al. (2025) highlight several limitations with these optimization-based approaches. Optimization depends on a chosen factor model and covariance matrix, potentially skewing the portfolio toward volatility management rather than carbon reduction. Since weight adjustments respond primarily to changes in measured risk rather than decarbonization impact, sudden price swings can trigger volatility-driven reallocation. Small variations in the risk model often yield materially different portfolios. To avoid these issues, we adopt a rule-based screen in which firms are ranked by RCP, and those below a threshold are excluded.

Rule-based exclusion enhances transparency by providing clear criteria that allow investors and regulators to identify excluded firms without relying on black-box optimizers. It also limits unintended style drift, where tracking-error constraints may tilt sector or factor exposures toward low-covariance assets, creating uncompensated bets unrelated to carbon reduction. Engagement remains credible since high emitters cannot benefit from transiently low covariance estimates. In addition, exclusions only occur when a firm crosses the RCP threshold, which limits turnover, avoids trades driven by changing risk forecasts, and reduces transaction costs.

As previously noted, carbon emissions - and thus RCP - are updated annually at the start of the third quarter, based on the most recently reported fiscal year $t-1$. On date t, monthly benchmark constituents are indexed by $i = 1, \ldots, N_t$ with benchmark weights $w_{i,t}^{bm}$ and corresponding $RCP_{i,t}$ scores. We exclude firms with RCP below the threshold $q_{\theta,t}$, where θ represents the chosen proportion of the benchmark's market cap to retain (for example, $\theta = 90\%$). The threshold $q_{\theta,t}$ is defined as

$$q_{\theta,t} = \inf \left\{ s \mid \sum_{i=1}^{N_t} w_{i,t}^{bm} 1_{\{RCP_{i,t} \geq s\}} \leq \theta \right\}. \tag{6}$$

Equation (6) gives the smallest RCP score s such that the benchmark weight of firms with $RCP_{i,t} \geq s$ is no greater than θ. Firms with scores below this cutoff form the subset L of *low-RCP* firms to be excluded, while those above form the subset H of *high-RCP* firms that are allocated higher weights within their peer groups. This notation is used throughout to separate excluded from overweighted firms. To identify the firms in L, we define

$$I_{L,t} = \left\{ 1_{\{RCP_{i,t} < q_{\theta,t}\}} \right\}_{i=1}^{N_t}.$$

Here, $I_{L,t}$ is a vector of indicator functions for each firm i in the benchmark, where the indicator equals 1 if $RCP_{i,t}$ is below the threshold $q_{\theta,t}$, and 0 otherwise. Therefore, the set $I_{L,t}$ serves as a definitive list of all the low-performing firms that will be removed from the portfolio. Once this list is defined, we proceed to exclude firms based on their market weights. Given θ, we order all firms by increasing RCP and sum their benchmark weights until the cumulative weight reaches $1-\theta$, thereby excluding that fraction of the benchmark's total market value.

We consider three thresholds, $\theta = 0.99$, 0.90, and 0.75, which correspond to excluding the lowest 1%, 10%, and 25% of benchmark market value according to their RCP ranking. At the close of each month, we rank holdings by RCP and apply the exclusion rule. Firms that improve their RCP may re-enter the investable universe once they are no longer in the bottom share.

After exclusions, two reinvestment strategies are considered. In the pure exclusion strategy, the proceeds are redistributed proportionally across the remaining benchmark constituents. In the best-in-class strategy, the excluded weight $1-\theta$ is reinvested in the highest RCP firms within the same region and sector, preserving benchmark exposures and limiting unintended shifts in risk. The design and implementation of both strategies are detailed below.

4.3. Proportionate Reinvestment under the Pure Exclusion Strategy

The proceeds from excluding firms, which equal a fraction $(1-\theta)$ of the benchmark market value, are reallocated proportionately to the stocks that remain in the portfolio. The weight vector for the pure exclusion portfolio is

$$w_{i,t}^{p} = \begin{cases} 0 & \text{for } i \in I_{L,t} \text{ with } \sum_{i \in I_{L,t}} w_{i,t}^{bm} \approx 1-\theta, \\ w_{i,t}^{bm}\left(\frac{1}{\sum_{i \in I_{I,t}} w_{i,t}^{bm}}\right) & \text{for } i \in I_{I,t}. \end{cases}$$

The new portfolio weights $w_{i,t}^{p}$ are best understood by considering two cases. First, any firm i in the exclusion set $I_{L,t}$ receives zero weight. Second, the exclusion set is defined so that the total benchmark weight of removed firms comes as close to $1-\theta$ as possible without exceeding that threshold. Each included firm $i \in I_{I,t}$ retains its benchmark weight $w_{i,t}^{bm}$ but is scaled by the reciprocal of the total weight of all included firms. Since we remove firms whose combined weight is about $1-\theta$, the remaining weights sum to roughly θ. Dividing by this number inflates the original weights of the remaining firms so that the new weights sum to one. To evaluate portfolio performance, we measure returns over month $t+1$. The ex-post total return for each portfolio is computed as the weighted average of individual stock returns, including dividends, where weights correspond to their benchmark or portfolio allocations at time t.

4.4. Regional/Sectoral Reinvestment under the best-in-class Strategy

Building on the best-in-class framework in Fahlenbrach and Jondeau (2023) and Jondeau et al. (2025), we implement a strategy that reallocates capital from excluded low-RCP firms to high-RCP peers within the same region and sector. Let R_i denote the region of firm i, and S_i the corresponding sector classification. The indicator variable $1_{R_i=r,S_i=s}$ equals 1 if firm i belongs to region r and sector s, and 0 otherwise. We define the set of firms in a given region r and sector s as $I_t(r,s) = \{1_{R_i=r,S_i=s}\}_{i=1}^{N_t}$ for any r and s.

The set of firms to be excluded is

$$I_{L,t}(r,s) = \left\{ 1_{\{R_i=r,\, S_i=s,\, RCP_{i,t} < q_{1-\theta_t(r,s),t}\}} \right\}_{i=1}^{N_t},$$

where

$$\theta_t(r,s) = \frac{\sum_{j \in I_{L,t}(r,s)} w_{j,t}^{bm}}{\sum_{j \in I_t(r,s)} w_{j,t}^{bm}}$$

represents the proportion of market value excluded from region–sector (r,s). While the excluded firms are the same as in the PX strategy, capital is reallocated only within the corresponding region–sector, favoring firms with higher RCP. This maintains constant segment weights. For example, if 5% of industrials in emerging markets are excluded, that capital is reallocated to the top-RCP industrials in the same market. The overweighted set of firms is $I_{H,t}(r,s) = \left\{ 1_{R_i=r,S_i=s,RCP_{i,t} \geq q_{\theta_t(r,s),t}} \right\}_{i=1}^{N_t}$. The overall sets are $I_{H,t} = \{I_{H,t}(r,s)\}_{r,s}$ and $I_{L,t} = \{I_{L,t}(r,s)\}_{r,s}$. The regional/sectoral reinvestment strategy is defined as follows

$$w_{i,t}^{p} = \begin{cases} 0 & \text{for } i \in I_{L,t} \text{ with } \displaystyle\sum_{i \in I_{L,t}} w_{i,t}^{bm} \approx 1-\theta, \\ w_{i,t}^{bm} & \text{for } i \in I_{I,t}, \\ w_{i,t}^{bm}\left(1 + \dfrac{\displaystyle\sum_{j \in I_{L,t}(R_i,S_i)} w_{j,t}^{bm}}{\displaystyle\sum_{j \in I_{H,t}(R_i,S_i)} w_{j,t}^{bm}}\right) & \text{for } i \in I_{H,t}. \end{cases}$$

The best-in-class portfolio weights are determined by these three categories. The first case applies to firms in the exclusion list $I_{L,t}$, where any firm i with low RCP has its weight set to zero, and the total weight of all excluded firms is approximately θ. The second case applies to firms that are neither excluded nor designated as best-in-class, $I_{I,t}$. These firms retain their original benchmark weight $w_{i,t}^{bm}$. The third case applies to the firms with the highest RCP within their region–sector, those in $I_{H,t}$, who are considered best-in-class. For this third category of firms, the benchmark weight is proportionally increased by the relative market value of the excluded peers within the same region–sector. This adjustment ensures that the cumulative region–sector weight remains consistent with the benchmark allocation. From an investor's perspective, the attractiveness of this strategy lies in maintaining sectoral and regional neutrality while rewarding the most carbon-efficient firms.

5. Results

5.1. PX Strategy Results

5.1.1. Performance Summary

Table 3 reports the results for the pure exclusion strategy. At the 99% and 90% thresholds, total return and total risk remain close to the benchmark, consistent with the objective defined earlier; the strategy removes the lowest-ranked RCP firms and redistributes weights across the remaining universe while keeping broad market exposure. At the 75% threshold, there is a small rise in total return together with a modest increase in total risk. The return-to-risk ratio remains confined to a narrow range, and the Sharpe ratio remains similar to the benchmark at all cutoffs, with only a slight decline at the strictest exclusion level. These outcomes indicate that RCP-based exclusion preserves diversification by maintaining a sufficiently wide investable universe after removing only the lowest-ranked firms, despite the absence of explicit sector or regional constraints. The results support prior findings that portfolios with extreme environmental tilts experience higher total risk without proportional gains in risk-adjusted returns (Görgen et al., 2021). They also align with recent work on net-zero benchmarks showing that removing heavy emitters can substantially reduce footprints while keeping ex-post risk-adjusted returns largely intact (Jondeau et al., 2025).

The analysis of tracking performance provides similar results. Average active returns are close to zero at the less and moderately restrictive thresholds and remain small at the most restrictive threshold. Tracking error rises progressively as exclusions become stricter, as expected. At the 99% threshold, the dispersion of active returns is only a few basis points, at 90% it stays below one percent, and at 75% it rises but remains in a range consistent with a constrained tilt rather than a shift in style. This is consistent with Blitz and Swinkels (2021), who show that low tracking error produces a negligible expected return loss, while higher tracking error levels introduce economically meaningful expected return reductions due to under-diversification. The information ratios are small in absolute value, which is expected given that the construction rule does not target expected alpha. The benchmark already explains most of the return variation, leaving limited scope for systematic outperformance. Beta is close to unity for the moderate restriction levels, and only slightly above one at 75%. Since the PX strategy changes weights within the investable set without imposing explicit allocation targets, market exposure should remain near one.

Table 3: Summary statistics for the Pure Exclusion (PX) strategy. The table reports average values over the full sample period for portfolio performance, portfolio characteristics, tracking analysis, carbon metrics, and factor exposures. Results are reported for the benchmark and for PX portfolios constructed at the 99%, 90%, and 75% RCP thresholds. Definitions of selected portfolio metrics are provided in Appendix A. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Significance levels correspond to H_0: $\beta = 0$ for all factors, except for MKT–RF, where H_0: $\beta = 1$.

Metric	**Benchmark**	**PX 99%**	**PX 90%**	**PX 75%**
Return and Risk				
Total return (%)	17.49	17.45	17.54	17.87
Total risk (%)	14.29	14.25	14.31	14.98
Return/risk	1.224	1.225	1.225	1.193
Sharpe ratio	1.207	1.208	1.208	1.177
Max drawdown (%)	-20.36	-20.06	-19.96	-22.10
Portfolio Characteristics				
Average number of positions	2047	1748	1465	1199
Effective number of positions	252	230	196	160
Top-ten weight (%)	13.67	14.45	15.93	18.49
Turnover (%)	10.94	10.96	11.76	14.41
Tracking Analysis				
Active return (%)	–	-0.04	0.04	0.38
Tracking error (%)	–	0.32	0.56	1.47
Information ratio	–	-0.12	0.08	0.26
Historical beta	–	1.00	1.00	1.04
Carbon Metrics				
WACI change (%)	–	3.05	-27.46	-62.18
CF change (%)	–	-6.89	-41.29	-60.06
CI change (%)	–	-3.75	-39.99	-61.03
Factor Exposures				
Alpha	0.005***	0.005***	0.005***	0.005***
MKT-RF	0.977**	0.975**	0.976**	1.006
SMB	-0.127***	-0.135***	-0.171***	-0.200***
HML	-0.085**	-0.075*	-0.068*	-0.089***
RMW	0.037	0.048	0.031	-0.018
CMA	0.096*	0.106*	0.089	0.010
WML	-0.035**	-0.033**	-0.036**	-0.059***
R^2	0.992	0.991	0.992	0.990
Obs.	124	124	124	124

Portfolio characteristics help explain why risk remains contained. The number of positions declines as the screen tightens, which follows directly from the rank-based exclusion. The effective number of positions does, however, fall by less than the simple count, which implies that the remaining weights are spread across many firms and that exposure is preserved for longer than a one-for-one removal would suggest. Top-ten concentration rises under tighter exclusion levels, which is expected when the strategy removes part of the tail and reweights the remaining portion of the distribution. Turnover is modest at the less and moderately restrictive thresholds and increases at 75%, reflecting stronger rebalancing pressure when more firms are excluded. Drawdowns are close to the benchmark at 99% and 90%, and widen only moderately at the 75% level. In absolute terms, the gap is small at the less restrictive thresholds and remains within the range typically expected for an enhanced index approach. These features align with the implementation goal of controlling active risk while achieving material reductions in portfolio-level carbon measures.

Factor regressions provide an external check on unintended bets. Market exposure remains close to one and is statistically below unity for the 99% and 90% thresholds, but not at the 75% threshold. Negative size tilts increase in magnitude as the exclusion rule becomes more restrictive. These results are consistent with the interpretation that exclusions affect both large emitters and smaller low-RCP firms, producing a mild negative size tilt at the higher thresholds and a more pronounced tilt under the strictest exclusion rule. Value exposure is slightly negative, with no systematic trend across thresholds. Profitability and investment factors have small loadings; CMA is weakly positive and statistically significant at the less restrictive thresholds and close to zero at the most restrictive. Momentum is slightly to moderately negative across all cutoffs, with a larger magnitude at the tightest screen. The high R^2 shows that priced factors explain most of the variation in excess returns. The combination of small tilts, low tracking error at moderate screens, and largely stable Sharpe ratios indicates that the PX portfolios keep relatively constant exposure to the main compensated risk factors while reducing exposure to the carbon metrics. This matches prior studies showing that exclusionary screens can unintentionally load against value and related factors, but that limited exclusions keep such tilts small with return patterns largely driven by common factor exposures rather than carbon screens per se (Blitz and Swinkels, 2021; Görgen et al., 2021). Optional guardrails, such as single-firm caps or turnover budgets, could be used to further stabilize outcomes without changing the main conclusions.

Figure 4 shows the evolution of weighted-average carbon intensity, carbon footprint, and carbon intensity for the three portfolios from 2010 to 2024. The relative ordering of the portfolios remains stable, with the 99% threshold nearly identical to the benchmark and the 90% and 75% thresholds showing a material reduction in financed emissions. The close co-movement of the three measures indicates that the results reflect a broad shift in portfolio composition instead of metric-specific effects.

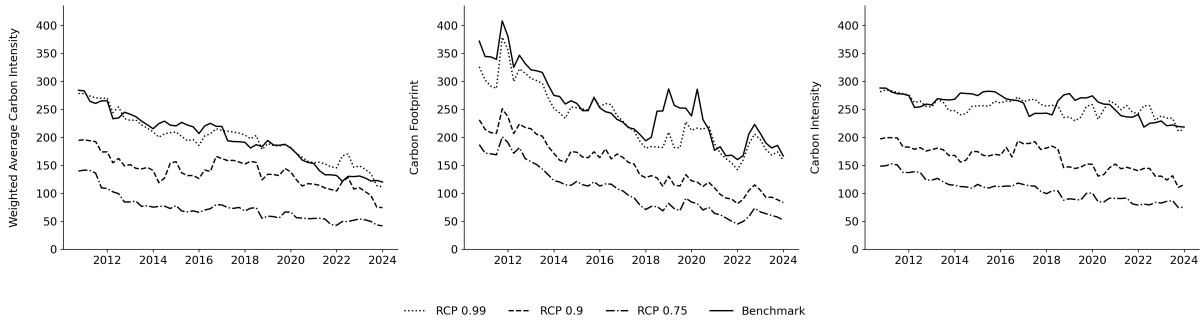


Figure 4: Quarterly weighted-average carbon intensity, carbon footprint, and carbon intensity for MSCI ACWI portfolios under pure exclusion at RCP thresholds of 75%, 90%, and 99% versus the benchmark, from 2010 to 2024.

5.1.2. Performance Attribution Analysis

Table 4 indicates that sector-level active returns are modest across thresholds under the PX strategy. At the 75% threshold, the positive total is concentrated in Information Technology and Financials. The attribution analysis shows that these gains are mainly from the allocation component that follows proportional scaling after exclusions, while the selection contributions are close to zero on average. Industrials and Consumer Discretionary contribute marginally to performance, and Energy, Health Care, and Consumer Staples have slightly negative contributions at this tight screen. Allocation effects remain small and concentrated within a few sectors, with sector weights broadly matching the benchmark. The differences are even smaller when we move to the 90% threshold, and ordering is largely preserved. Information Technology still demonstrates a small positive selection effect, Financials have a modest positive total contribution that is mostly allocation-driven, and the majority of other sectors show effects near zero. At the 99% threshold, sector contributions are near neutral as holdings converge toward the benchmark.

The cross-sectional pattern in Table 4 helps clarify how the exclusion strategy shapes allocation and selection outcomes across sectors. Where the dispersion in RCP ranks within a sector is wider, like-for-like replacement can generate selection effects when it occurs. Where dispersion is narrower or exclusions bind more tightly, proportional scaling of benchmark weights explains a larger share of the small totals. The concentration of high emitters in a small group of firms and industries highlights the importance of sectoral heterogeneity, consistent with Jagannathan et al. (2025). On average, allocation is governed by the benchmark and reflects proportional scaling rather than explicit tilts.

Appendix B Table A2 shows that geographic effects are limited and mostly follow from proportional scaling. The U.S. segment accounts for the largest share of the positive effects at the 75% and 90% thresholds. Japan and the United Kingdom also contribute small positives, while most other regions remain close to zero. At 99%, contributions across all countries are essentially neutral. This confirms that the PX strategy does not introduce active country tilts, and that deviations in active return mainly reflect how benchmark weights adjust through scaling.

Table 4: Performance attribution analysis by sector for Pure Exclusion portfolios at thresholds 75%, 90%, and 99% relative to the common benchmark. The table reports benchmark sector weights and returns, portfolio weights and returns, and allocation, selection, and total effects. Benchmark sector weights and returns are constant across panels. "Return" reflects the sector's return, while "Total" is the contribution to portfolio return computed as weight × return and summed across sectors. "Allocation" reflects return from strategy reallocation vs. the benchmark, while "Selection" reflects return from stock performance within sectors at matched weights.

	Benchmark			Portfolio PX 75%			Attribution PX 75%		
Sector	Weight	Return	Total	Weight	Return	Total	Alloc.	Select.	Total
Energy	6.15	13.00	0.85	5.00	12.05	0.68	−0.15	−0.05	−0.20
Materials	4.67	13.26	0.68	4.79	13.46	0.72	0.02	0.01	0.03
Industrials	10.18	16.18	1.73	10.91	16.16	1.85	0.12	0.00	0.12
Consumer Discretionary	11.28	20.64	2.37	12.01	20.56	2.54	0.15	−0.01	0.14
Consumer Staples	9.17	11.85	1.16	7.89	12.29	1.02	−0.15	0.04	−0.12
Health Care	11.18	16.03	1.82	8.63	15.73	1.34	−0.41	−0.03	−0.43
Financials	18.05	15.11	2.80	20.41	14.79	2.88	0.36	−0.07	0.29
Information Technology	17.76	24.16	4.63	20.76	24.32	5.51	0.73	0.03	0.76
Communication Services	5.30	14.58	0.90	5.07	15.58	0.94	−0.03	0.05	0.02
Utilities	3.46	11.16	0.40	2.72	10.28	0.29	−0.08	−0.02	−0.11
Real Estate	2.80	5.57	0.16	1.80	5.97	0.10	−0.06	0.01	−0.05

	Portfolio PX 90%			Attribution PX 90%		
Sector	Weight	Return	Total	Alloc.	Select.	Total
Energy	6.23	12.72	0.84	0.01	−0.02	−0.01
Materials	4.46	13.25	0.65	−0.03	0.00	−0.03
Industrials	9.54	16.00	1.61	−0.10	−0.02	−0.12
Consumer Discretionary	11.22	20.94	2.41	−0.01	0.03	0.02
Consumer Staples	9.28	11.96	1.17	0.01	0.01	0.02
Health Care	10.48	15.38	1.63	−0.11	−0.07	−0.18
Financials	19.20	15.06	2.97	0.17	−0.01	0.16
Information Technology	17.84	24.34	4.72	0.02	0.03	0.05
Communication Services	5.66	14.92	0.98	0.05	0.02	0.07
Utilities	3.52	10.73	0.40	0.01	−0.02	−0.01
Real Estate	2.58	5.31	0.14	−0.01	−0.01	−0.02

	Portfolio PX 99%			Attribution PX 99%		
Sector	Weight	Return	Total	Alloc.	Select.	Total
Energy	6.19	12.85	0.83	0.01	−0.01	0.00
Materials	4.58	13.05	0.66	−0.01	−0.01	−0.02
Industrials	10.18	16.00	1.70	0.00	−0.02	−0.02
Consumer Discretionary	11.11	20.82	2.37	−0.04	0.02	−0.02
Consumer Staples	9.34	11.88	1.19	0.02	0.00	0.02
Health Care	11.21	15.79	1.79	0.01	−0.03	−0.02
Financials	17.70	15.05	2.75	−0.05	−0.01	−0.06
Information Technology	18.07	23.98	4.71	0.07	−0.03	0.04
Communication Services	5.35	14.66	0.90	0.01	0.00	0.01
Utilities	3.50	11.04	0.40	0.00	0.00	0.00
Real Estate	2.77	5.66	0.16	0.00	0.00	0.00

5.2. BIC Strategy Results

5.2.1. Performance Summary

Table 5 shows that the best-in-class strategy keeps risk close to the benchmark while delivering a small positive average active return at the 90% screen. The return-to-risk and Sharpe ratio both peak at this threshold, then move back toward benchmark levels as the screen tightens further. Tracking error remains low across all cutoffs, consistent with

the enhanced index profile implied by the reinvestment rule. Within each region–sector bucket, the low-RCP tail is excluded as in the PX strategy, but the proceeds are reallocated to the high-RCP set in proportion to benchmark weights. In notation, the excluded share $\theta_t(r, s)$ in bucket (r, s) is moved from $I_{L,t}(r, s)$ to $I_{H,t}(r, s)$ so that the bucket total equals its benchmark weight. Keeping region and sector totals fixed by construction limits allocation drift and helps explain why tracking error and drawdowns remain contained.

Table 5: Summary statistics for the best-in-class (BIC) strategy. The table reports average values over the full sample period for portfolio performance, portfolio characteristics, tracking analysis, carbon metrics, and factor exposures. Results are reported for the benchmark and for BIC portfolios constructed at the 99%, 90%, and 75% RCP thresholds. Definitions of selected portfolio metrics are provided in Appendix A. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Significance levels correspond to $H_0\colon\ \beta = 0$ for all factors, except for MKT–RF, where $H_0\colon\ \beta = 1$.

Metric	**Benchmark**	**BIC 99%**	**BIC 90%**	**BIC 75%**
Return and Risk				
Total return (%)	17.49	17.46	17.59	17.63
Total risk (%)	14.29	14.24	14.19	14.41
Return/risk	1.224	1.226	1.240	1.224
Sharpe ratio	1.207	1.209	1.223	1.207
Max drawdown (%)	-20.36	-20.07	-19.81	-20.28
Portfolio Characteristics				
Average number of positions	2047	1749	1476	1217
Effective number of positions	252	233	209	176
Top-ten weight (%)	13.67	14.33	15.19	17.29
Turnover (%)	10.94	11.18	12.89	16.44
Tracking Analysis				
Active return (%)	–	-0.03	0.10	0.14
Tracking error (%)	–	0.31	0.53	0.81
Information ratio	–	-0.11	0.18	0.17
Historical beta	–	1.00	0.99	1.01
Carbon Metrics				
WACI change (%)	–	2.10	-30.42	-58.57
CF change (%)	–	-7.58	-42.34	-56.26
CI change (%)	–	-5.12	-44.92	-61.08
Factor Exposures				
Alpha	0.005***	0.005***	0.005***	0.005***
MKT-RF	0.977**	0.975**	0.972**	0.986
SMB	-0.127***	-0.134***	-0.127***	-0.117***
HML	-0.085**	-0.076*	-0.067	-0.082***
RMW	0.037	0.050	0.065	0.056
CMA	0.096*	0.106*	0.099*	0.105**
WML	-0.035**	-0.032*	-0.025	-0.032
R^2	0.992	0.992	0.991	0.992
Obs.	124	124	124	124

Portfolio statistics align with the purpose of the within-bucket reinvestment rule and illustrate how the BIC strategy differs from the PX strategy in practice. The number of holdings and the effective number of positions decline as the screen tightens, yet both

remain higher than under the PX strategy at the same thresholds because the reinvestment keeps the buckets intact. Top-ten concentration rises more slowly than under the PX strategy, since scaling occurs across many best-in-class firms. Turnover increases at 90% and 75%. Holding sector and country weights fixed preserves exposure and keeps tracking error modest as carbon metrics decline. These findings are consistent with Jondeau et al. (2025). Given that the top 10% of firms account for over 86% of Scope 1 + 2 emissions, trimming the right tail materially lowers the portfolio's carbon footprint with minimal loss of market exposure (illustrated in Appendix B, Figure A4).

Factor regressions provide further support for the intended neutrality. Market beta is close to unity, and the size loadings remain negative and broadly stable. Value, profitability, and momentum loadings are small, and the investment factor (CMA) is positive and statistically significant across thresholds. The pattern is consistent with research indicating that exclusions may unintentionally reduce exposure to rewarded factors, an outcome that can be mitigated by tilting toward close substitutes, and that carbon-risk exposures are correlated with common factors (Blitz and Swinkels, 2021; Görgen et al., 2021). The high R^2 shows that priced factors explain almost all excess-return variation, analogous to what is observed for the PX strategy.

Figure 5 shows that the BIC strategy achieves reductions in carbon metrics across thresholds that are comparable to those under PX (see Figure 4). With the 90% screen, both strategies achieve substantial carbon reductions relative to the benchmark with low tracking error. The PX strategy is easier to implement and communicate to clients, whereas the BIC strategy upholds greater diversification and stability.

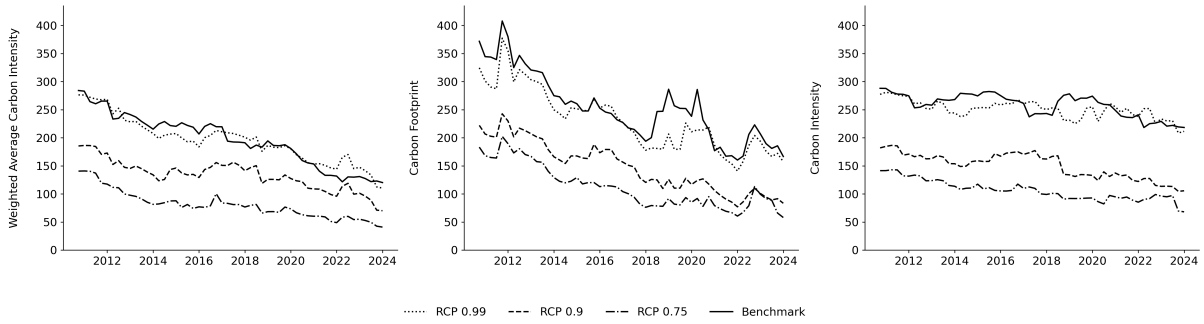


Figure 5: Quarterly weighted-average carbon intensity, carbon footprint, and carbon intensity for MSCI ACWI portfolios under best-in-class at RCP thresholds 75%, 90%, and 99% versus the benchmark, from 2010 to 2024.

5.2.2. Performance Attribution Analysis

Table 6 indicates that sector attribution effects for the BIC strategy are small in the aggregate and mostly associated with selection rather than allocation effects. With the moderate screen, Consumer Staples shows the clearest selection gain, while Information Technology adds a small net positive contribution that is partly allocation-driven. Industrials and Communication Services show modest positive selection effects, while Energy, Health Care, and Financials are slightly negative. Allocation effects remain small by construction, and sector weights stay close to the benchmark.

Table 6: Performance attribution analysis by sector for best-in-class portfolios at thresholds 75%, 90%, and 99% relative to the common benchmark. The table reports benchmark sector weights and returns, portfolio weights and returns, and allocation, selection, and total effects. Benchmark sector weights and returns are constant across panels. "Return" reflects the sector's return, while "Total" is the contribution to portfolio return computed as weight × return and summed across sectors. "Allocation" reflects return from strategy reallocation vs. the benchmark, while "Selection" reflects return from stock performance within sectors at matched weights.

	Benchmark			Portfolio BIC 75%			Attribution BIC 75%		
Sector	Weight	Return	Total	Weight	Return	Total	Alloc.	Select.	Total
Energy	6.15	13.00	0.85	6.16	12.14	0.81	0.00	−0.05	−0.05
Materials	4.67	13.26	0.68	4.56	13.67	0.69	−0.02	0.02	0.00
Industrials	10.18	16.18	1.73	10.10	16.54	1.75	−0.01	0.04	0.02
Consumer Discretionary	11.28	20.64	2.37	11.20	20.66	2.38	−0.02	0.00	−0.01
Consumer Staples	9.17	11.85	1.16	9.30	12.94	1.27	0.01	0.10	0.12
Health Care	11.18	16.03	1.82	11.18	15.56	1.75	0.00	−0.05	−0.05
Financials	18.05	15.11	2.80	18.06	14.80	2.76	0.00	−0.06	−0.06
Information Technology	17.76	24.16	4.63	17.93	24.27	4.75	0.04	0.02	0.06
Communication Services	5.30	14.58	0.90	5.29	15.21	0.92	0.00	0.03	0.03
Utilities	3.46	11.16	0.40	3.47	10.76	0.39	0.00	−0.01	−0.01
Real Estate	2.80	5.57	0.16	2.76	6.18	0.18	0.00	0.02	0.01
				Portfolio BIC 90%			Attribution BIC 90%		
Sector				Weight	Return	Total	Alloc.	Select.	Total
Energy				6.16	12.96	0.84	0.00	0.00	0.00
Materials				4.56	13.58	0.69	−0.02	0.01	0.00
Industrials				10.10	16.41	1.74	−0.01	0.02	0.01
Consumer Discretionary				11.20	20.77	2.39	−0.02	0.01	0.00
Consumer Staples				9.30	12.31	1.22	0.01	0.04	0.06
Health Care				11.18	15.16	1.71	0.00	−0.10	−0.10
Financials				18.06	15.22	2.83	0.00	0.02	0.02
Information Technology				17.93	24.11	4.72	0.04	−0.01	0.03
Communication Services				5.29	14.77	0.90	0.00	0.01	0.01
Utilities				3.47	11.06	0.40	0.00	0.00	0.00
Real Estate				2.76	5.44	0.15	0.00	0.00	−0.01
				Portfolio BIC 99%			Attribution BIC 99%		
Sector				Weight	Return	Total	Alloc.	Select.	Total
Energy				6.16	12.81	0.82	0.00	−0.01	−0.01
Materials				4.56	13.06	0.66	−0.02	−0.01	−0.02
Industrials				10.10	15.97	1.69	−0.01	−0.02	−0.03
Consumer Discretionary				11.20	20.83	2.39	−0.02	0.02	0.01
Consumer Staples				9.30	11.92	1.18	0.01	0.01	0.02
Health Care				11.18	15.69	1.77	0.00	−0.04	−0.04
Financials				18.06	15.21	2.83	0.00	0.02	0.02
Information Technology				17.93	24.00	4.67	0.04	−0.03	0.01
Communication Services				5.29	14.65	0.89	0.00	0.00	0.00
Utilities				3.46	11.04	0.40	0.00	0.00	0.00
Real Estate				2.76	5.70	0.16	0.00	0.00	0.00

At the 99% and 75% thresholds, sector totals are near zero. At the less restrictive threshold, within-sector substitutions are limited and tend to offset. At the more restrictive threshold, the feasible range within some industries narrows, which reduces the scope for selection. Energy and Utilities remain close to neutral on both legs, while sectors with wider RCP dispersion, such as Consumer Staples and Information Technology, appear to offer more room for modest selection gains. Overall, Table 6 supports the view that

the BIC strategy decarbonizes through within-sector reweighting while keeping sector exposures close to benchmark levels. Any small positive active returns at the moderate screen are consistent with systematic stock selection rather than sector rotation. This mechanism parallels the PX strategy, but the BIC strategy targets neutrality across region–sector buckets. Variation in RCP ranks across sectors and major markets allows within-bucket upgrades that raise carbon profitability without shifting broad exposures. Sectors with wider RCP dispersion, such as Consumer Staples and Information Technology, account for most of the modest positive selection at the moderate screen.[9] This structure suggests that active risk is largely idiosyncratic in normal states. If transition shocks become more systematic, for example if commodity or policy uncertainty increases co-movement among high emitters, the carbon-related common component may rise. One potential weakness of the strategy is that selections may co-move with the green factor documented by Pástor et al. (2022), and reduced exposure to high emitters may forgo the carbon premium discussed by Bolton and Kacperczyk (2021).

6. Robustness Across Markets and Signals

6.1. Regional Analysis

Figure 6 displays return and risk characteristics for RCP-based portfolios constructed from the ACWI, North America, Europe, and Pacific indices under the BIC and PX strategies. The ordering of portfolios by threshold is stable across all markets. The BIC strategy stays closer to the benchmark than the PX strategy across all thresholds. Periods of higher tracking error align with narrow market leadership when a small set of industries drives index returns. These patterns match the mechanism emphasized earlier: when the effective range is preserved and firm concentration is moderate, selection within industries carries most of the load and active risk remains contained. Regional results follow the same pattern across markets (detailed summary tables are provided in Appendix D, Tables A6 and A7).

The columns with ACWI graphs in Panel A and Panel B of Figure 6 summarize the global signal. Under the BIC strategy, cumulative excess returns drift slowly upwards at the 90%, remain close to flat at the 99%, and decrease moderately at the 75% threshold. Tracking error scales with screen tightness and is uniformly higher under the PX strategy relative to BIC. The PX strategy follows the same pattern, though the magnitudes are larger. At the 75% threshold, cumulative excess returns rise gradually through the sample, while rolling tracking error increases but remains within a range consistent with enhanced index mandates. The global result is therefore not driven by one region; it is an aggregation of small selection effects over time.

[9]Country-level attribution in Appendix B Table A3 follows the sector patterns but with smaller magnitudes, since the BIC design keeps region–sector totals fixed and channels active return toward stock selection. At the 75% threshold, the United States provides the main contribution, with modest positives in Japan and Switzerland and near-zero effects elsewhere.

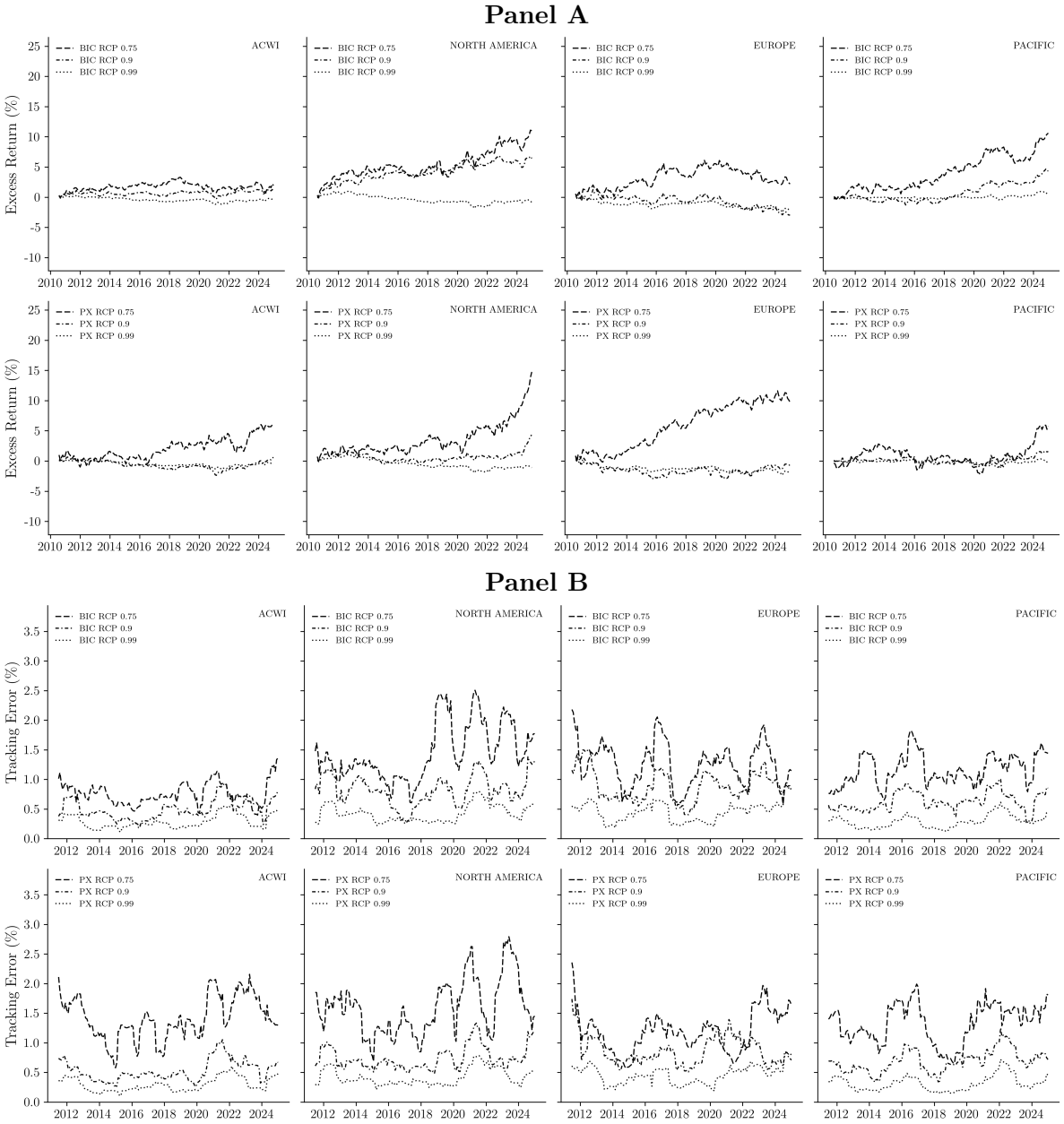


Figure 6: Results for RCP-based portfolios by region and construction method. Panel A plots cumulative excess return relative to the relevant regional benchmark. Panel B plots 12-month rolling tracking error. Portfolios are constructed using Relative Carbon Profitability thresholds of 75%, 90%, and 99% across ACWI, North America, Europe, and the Pacific. Both panels report best-in-class and Pure Exclusion portfolios built from the same investable universe.

Turning to the regional indices, the plots for North America, Europe, and the Pacific provide additional insight. North America provides the most demanding setting for strict PX screening, where the 75% PX portfolio produces the largest cumulative excess return and the highest tracking error among the regions. The opposite pattern is found for Europe, where the 75% PX portfolio exhibits a rising cumulative path that stabilizes around 2015 at a higher level. Tracking error is lower than in North America, partly as a result of wider RCP dispersion in sectors such as Industrials, Consumer Discretionary, and Materials, and a less concentrated benchmark. The Pacific region falls between these

two cases. In this region, results lie between the two preceding cases. Both strategies generate cumulative excess returns near zero at the 90% and mildly positive outcomes at the 75% threshold. Across all three regions, the BIC strategy consistently reduces active risk relative to PX at a given threshold.

In sum, the results suggest a common ranking of strategies across regions and thresholds. The BIC strategy at 99% remains the most conservative design, delivering steady reductions in carbon metrics with minimal tracking error. The PX strategy with a 75% threshold generates the largest cumulative excess return differences when market structure allows, with a corresponding rise in active risk that is most prominent in North America. The slope of cumulative excess returns and the level of rolling tracking error tend to move together, particularly at the strict thresholds. In the middle range, especially for the BIC strategy at the 90% threshold, investors may obtain small but persistent cumulative gains alongside limited active risk across markets.

6.2. Carbon Intensity versus Relative Carbon Profitability

We supplement the analysis by replicating the investment strategies using carbon intensity rather than Relative Carbon Profitability as the exclusion criterion. All portfolios retain identical benchmarks, constraints, and rebalancing rules as in the baseline specification, allowing for direct comparison with our earlier results to isolate differences that stem from the information content of the signals and their interaction with sectoral and regional structures (see Appendix B, Tables A4 and A5 for full results). Average total return is slightly higher with CI as the exclusion criterion, particularly at more restrictive thresholds, and most visibly under the PX strategy. Across thresholds, CI delivers slightly higher total returns than RCP in both PX and BIC portfolios, but the differences are small and not central to the strategy evaluation. The route to decarbonization therefore matters for both interpretation and governance. Under RCP, within-sector substitution dominates and maintains exposure to hard-to-abate industries. CI shifts capital across sectors and thereby increases allocation-driven risk and the sensitivity of tracking error at tighter thresholds. The underlying return drivers also differ across the two exclusion metrics. Tables A4 and A5 in Appendix B document that CI portfolios load more negatively on SMB and HML at the tighter threshold than the corresponding RCP portfolios. The negative SMB loading reflects a systematic shift toward larger firms, while the more negative HML coefficient signals a stronger rotation into growth-oriented sectors. These patterns are consistent with CI reallocating capital across sectors, particularly toward industries such as Information Technology and Health Care. The RCP portfolios remain closer to benchmark exposures, as their decarbonization occurs primarily through within-sector replacement rather than broad reallocation. The regional portfolios show a similar pattern and confirm the robustness of these findings (results omitted for brevity).

Table 7 Panel A shows the sector shifts induced by CI at strict thresholds. The exposure to the Energy sector declines sharply from around six percent in the benchmark to less than one percent at the 75% CI threshold. Offsetting increases occur in sectors such as Information Technology, Financials, and Health Care. The RCP portfolios in the same panel remain much closer to benchmark weights, even at the 75% threshold.

Panel B reports country weights under the same strategy. U.S. equity exposure rises from 55.5% in the benchmark to 58.6% in the 75% CI portfolio, while the corresponding RCP portfolio stays much closer to benchmark allocations. These cross-checks indicate that a larger share of active risk is driven by allocation effects rather than firm-level selection. In a global composite, country-level shifts can appear limited because reallocations in one region are often offset by movements in another, reducing the visibility of the underlying adjustments. For asset managers operating with regional benchmarks, these tilts can therefore have a more noticeable influence on active risk and relative performance.

Table 7: Average sector and country weights in percent for the global benchmark (BM) and for portfolios constructed using carbon intensity (CI) and Relative Carbon Profitability (RCP) as screening criteria under the pure exclusion strategy. The table reports ACWI results in two panels. Panel A lists the eleven GICS sectors, with sector codes mapped to firms during data construction. Panel B lists the largest benchmark countries by average weight. Columns report BM together with CI 99%, CI 90%, CI 75%, and RCP 99%, RCP 90%, RCP 75%. Weights are averages over the sample and reflect the same benchmark, constraints, and rebalancing choices as in the baseline specification. Within each panel, weights in each column sum to 100%, subject to minor rounding differences.

	BM	**CI 99%**	**CI 90%**	**CI 75%**	**RCP 99%**	**RCP 90%**	**RCP 75%**
Panel A: ACWI sectors							
Energy	6.15	6.22	3.84	0.44	6.18	6.23	5.00
Materials	4.67	4.43	1.95	0.56	4.58	4.46	4.79
Industrials	10.18	10.20	9.93	9.24	10.18	9.54	10.91
Consumer Discretionary	11.28	11.32	12.24	13.65	11.10	11.22	12.01
Consumer Staples	9.17	9.39	10.36	8.72	9.34	9.28	7.89
Health Care	11.18	11.30	12.48	14.23	11.21	10.48	8.63
Financials	18.05	18.25	19.78	23.12	17.70	19.20	20.41
Information Technology	17.76	18.12	19.90	21.26	18.07	17.84	20.76
Communication Services	5.30	5.35	5.92	6.68	5.35	5.66	5.07
Utilities	3.46	2.61	0.73	0.09	3.50	3.52	2.72
Real Estate	2.80	2.79	2.87	2.00	2.77	2.58	1.80
Panel B: ACWI countries							
USA	55.52	55.88	56.57	58.61	55.84	56.63	56.26
Japan	8.37	8.66	9.05	9.06	8.68	8.79	9.36
United Kingdom	4.80	4.82	4.91	4.90	4.81	5.26	5.75
France	3.62	3.77	3.79	3.81	3.77	3.95	4.09
Switzerland	3.05	3.06	3.38	3.28	3.10	3.30	2.86
Canada	3.02	2.99	2.46	2.56	3.01	2.84	2.86
Germany	3.02	3.02	3.09	2.85	3.00	2.90	3.05
Australia	2.55	2.60	2.36	2.36	2.62	2.49	2.57
Korea	1.77	1.78	1.77	1.48	1.77	1.40	1.36
Taiwan	1.70	1.75	1.71	1.01	1.74	1.01	0.99
China	1.61	1.34	1.38	1.23	1.33	1.22	1.22

Taken together, the results show that carbon intensity is a weak primary exclusion signal when the goal is to decarbonize portfolios while preserving intended factor and allocation exposures. CI lowers WACI mainly by shifting capital across sectors and regions, which increases active risk and creates a stronger concentration of benchmark weights -

effects that are difficult to justify as a climate signal. The modest return differences that sometimes favor CI stem from allocation effects and disappear once these are controlled for. The findings on concentration, factor loadings, and attribution support this interpretation and point to RCP as the more robust signal for portfolio decarbonization under realistic tracking-error limits and governance constraints.

6.3. Limitations

Despite the robustness checks discussed in the previous section, our findings should be viewed in light of limitations associated with data quality, methodological constraints, and the scope for interpretation. A key constraint concerns the reliability of carbon data. Corporate emissions are reported with lags and differ across data providers. Methodological revisions and changes in reporting standards can also alter firm-level estimates and index composition without reflecting real changes in climate performance. Although an RCP-based screen appears less sensitive to short-term measurement noise than carbon intensity, it still depends on the accuracy of emissions data. RCP further relies on accounting earnings that include accruals and are affected by business cycle conditions, which can introduce cyclicality in rankings. While averaging over several periods could reduce short-term variation, it cannot completely eliminate the effect of temporary shocks.

Beyond these data-related issues, the empirical design relies on backtests that impose assumptions about data availability, corporate actions, free float, and currency conversion. Small deviations in these inputs can affect weights and performance metrics. The sample period may not capture structural shifts in climate policy, disclosure regulation, or investor preferences that shape future behavior. Policy changes, such as adjustments to carbon pricing or reporting frameworks, could reclassify both emissions and profitability and thereby influence the stability of the metric.

A further limitation relates to the broader applicability of the findings. The analysis is based on simulated portfolios under the PX and BIC strategies. Actual deployment adds transaction costs, liquidity constraints, capacity limits, and index reconstitution rules. Performance may vary across mandates with weak coverage or small peer groups, where neutrality to benchmark exposures is harder to maintain at tight thresholds.

7. Concluding Remarks

This paper evaluates a practical framework for lowering financed emissions in benchmark-constrained equity portfolios while preserving diversification and mandate consistency. The framework uses Relative Carbon Profitability (RCP), a firm-level signal introduced by Ang et al. (2024), that ranks firms by value generated per unit of carbon within their industry, and we implement this ranking as the exclusion criterion in portfolio construction. We evaluate two reinvestment strategies. The pure exclusion (PX) strategy removes the worst-ranked firms and redistributes weights proportionally to the remaining constituents. The best-in-class (BIC) strategy reinvests within the same sector and

region in higher-ranked peers, keeping benchmark exposures aligned. Across the analysis, both strategies achieve reductions in financed emissions with modest tracking error and turnover, near-neutral factor exposures, and benchmark-like drawdowns. The results show how decarbonization pressure interacts with allocation effects and implementation under specified tracking-error budgets.

The findings suggest three patterns that characterize the trade-off between emissions reduction and tracking error. First, both strategies reduce portfolio carbon measures by a sizeable amount. The risk profiles remain stable across market conditions, consistent with evidence that climate alignment shows little correlation with traditional return and volatility measures when portfolios remain diversified (Mercereau et al., 2020). Second, the trade-off between emissions reduction and tracking error depends on how reweighting is done. The PX strategy lowers financed emissions but can introduce allocation effects because excluded firms cluster in high-emitting industries, whereas the BIC strategy's like-for-like substitutions help reach a desired climate exposure while containing allocation effects, in line with Görgen et al. (2021). Our analysis also shows that tracking error rises faster as screening becomes more restrictive, especially in regional mandates constrained by a smaller investment universe. Third, the choice of signal matters for both efficiency and investability. Screening on carbon intensity tends to reduce exposure to Energy and Utilities and tilt toward low-emission sectors, which can create spurious alpha unless performance is adjusted for factor exposures and estimation error, a documented pitfall in low-carbon portfolio construction (Goltz et al., 2021). RCP maintains exposure to transition-relevant activities by reallocating toward more carbon-efficient firms within them.

The attribution analysis is consistent with these patterns. Under the BIC strategy, selection is the main source of any small active returns, while allocation effects remain small by construction. Turnover is modest by institutional norms, with portfolio adjustments occurring through numerous small reallocations rather than major position shifts. Factor regressions provide an external check on unintended exposures. Estimated betas to market, value, quality, investment, and momentum factors remain close to benchmark levels, indicating that no systematic tilt or persistent exposure explains the observed portfolio returns.

The regional portfolios indicate a practical boundary for implementers. North America, given its sector mix, is the strictest test of tight screens since a larger share of market value sits in industries with high operational or supply-chain emissions, while Europe is more accommodating. Using the BIC strategy helps mitigate these differences by enforcing like-for-like substitutions within each sector and region, though very restrictive thresholds still raise tracking error more in regional mandates than in the global composite. Defining thresholds based on tracking-error budgets at the mandate level keeps the approach consistent.

The results carry practical implications. For asset owners, the BIC strategy provides a balanced way to achieve decarbonization while preserving benchmark discipline, making it a suitable default for benchmark-constrained mandates. Thresholds can be linked to ex-ante tracking-error budgets with quarterly or semiannual rebalancing to match emissions data releases. Portfolio reports should include multiple carbon metrics and an attribution analysis alongside standard risk measures to verify that progress reflects within-sector stock selection rather than shifts in portfolio composition. For asset managers, execution quality matters. Processes that coordinate emissions updates, corporate actions, and index rebalances under disciplined trading can contain turnover and reduce slippage. For policymakers, the main implication relates to data quality. Broader and more reliable emissions coverage would improve the stability of portfolio signals, particularly where sectoral dispersion is high. More consistent underlying data would reinforce the mechanism through which sector-neutral decarbonization can be implemented for institutional investors.

Benchmark-level decarbonization is itself endogenous and path dependent. Over extended horizons, broad indices tend to decarbonize as technology, regulation, and disclosure evolve. If the underlying index decarbonizes rapidly in the coming decade, annual portfolio targets become easier to meet, whereas early progress tied to low-hanging opportunities may leave later reductions harder and costlier. These dynamics favor constructions that preserve benchmark exposures while pursuing annual reduction targets, as such designs remain more robust when the benchmark's trajectory is uncertain. Unusually difficult years will occur. Sector shocks and policy reversals can lift the benchmark's emissions in some periods and tighten the trade-off between the target, performance, and neutrality to the benchmark mix.[10] For a given reduction path, the reasonable set narrows as exclusions intensify, and tracking error rises when active weights concentrate. Conditioning the screen on value creation per unit of carbon moderates this mechanism by reducing structural underweights that come from business model clustering, yielding a more favorable carbon–tracking frontier. Even modest ex-ante tracking error can translate into periods of underperformance in stressed markets, so evaluation should span different regimes and portfolio designs.

Future research could extend this analysis by moving beyond historical backtests toward multi-objective portfolio models that balance financed emissions reduction against tracking error, liquidity, and turnover. A natural next step is to address the relationship between portfolio-level decarbonization and real-economy outcomes, since adjustments in ownership or capital allocation do not ensure firm-level emission reductions. Any effect operates through channels such as the cost of capital, market access, and reputation, and the strength of these channels depends on broader market participation and policy conditions. Continued improvements in data consistency and coverage, transparent esti-

[10] Appendix B Figure A5 shows that post-Paris emission trajectories diverge across major economies. Several large emerging markets continue to increase absolute emissions, which can contribute to short-run benchmark upticks when global indices are heavily weighted toward these regions.

mation of Scope 3, and systematic testing of carbon-risk scenarios would strengthen the reliability of the RCP metric. Incorporating forward-looking information on transition plans and exposure to regulatory or carbon-price pathways would allow the signal to capture expected trajectories rather than current levels alone. Further work could also examine implementation frictions such as trading costs, liquidity constraints, and capacity limits if many large investors adopt similar strategies, alongside robustness checks using point-in-time accounting data and alternative lag structures.

A key contribution of this analysis is to show how RCP enhances decarbonization by isolating firms with higher carbon-adjusted economic value within each sector. The BIC strategy in particular leverages this information, and preserves benchmark and factor structure for implementation. For institutional investors seeking credible climate alignment within fiduciary constraints, the resulting framework offers a transparent foundation that may evolve as data quality, disclosure practices, and investor coordination improve.

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Appendix A: Definition of Selected Portfolio Metrics

Tracking Error

The tracking error (also called active risk) measures the dispersion of excess returns of an index relative to its benchmark. It is defined as follows:

$$TE_{\text{ann}} = \sqrt{\sum_{t=1}^{n} \frac{12 * (R_t^A - \bar{R}^A)^2}{n-1}}$$

where

$$R_t^A = R_t^P - R_t^B$$

is the monthly active return of the index relative to its benchmark in month t.

Historical Beta

Beta measures the sensitivity of the index to movements in its benchmark. It is calculated as:

$$\beta = \text{Corr}(r_t^P, r_t^B) \cdot \frac{\sigma_{\text{ann}}^P}{\sigma_{\text{ann}}^B}$$

where $\text{Corr}(r_t^P, r_t^B)$ denotes the correlation between monthly returns of the index and the benchmark over the sample period.

Turnover

Turnover measures how much the index composition changes at each review. We report one-way turnover. Let I be the union of constituents before and after rebalancing. One-way turnover at date t is:

$$TO_t = \frac{1}{2} \times \sum_{i \in I} \left| \omega_{i,t}^{\text{opening}} - \omega_{i,t-1}^{\text{closing}} \right|,$$

where $\omega_{i,t}^{\text{opening}}$ is the opening weight after rebalancing (based on $t-1$ prices), and $\omega_{i,t-1}^{\text{closing}}$ is the closing weight before rebalancing. Reported turnover is annualized by multiplying the average per-review turnover by the number of rebalancing events per year. The dataset is monthly and spans 30/07/2010 to 31/12/2024.

Effective Number of Constituents

The effective number of constituents is a measure of index concentration, ranging from 1 (full concentration in one stock) to n (equal weights). It is computed as the inverse of the Herfindahl-Hirschman Index:

$$EN = \frac{1}{\sum_{i \in I} \omega_i^2}$$

where I is the set of index constituents and ω_i is the weight of stock i.

Appendix B: Additional Tables and Figures

Scope definitions and financed emissions

The figure illustrates how Scope 1, Scope 2, and Scope 3 emissions map onto a corporate value chain, separating upstream activities (e.g., inputs and suppliers) from downstream activities (e.g., product use and end-of-life treatment). Scope 3 also includes Category 15 (Investments), which attributes a share of a portfolio company's or borrower's emissions to the provider of capital and forms the basis for financed emissions reporting by financial institutions.

Two practical issues follow from this attribution. First, financed emissions require look-through estimates of portfolio company emissions and balance sheet allocation rules, which makes results sensitive to vendor assumptions and data availability. Second, Scope 3 accounting can generate systematic double counting: the same ton of CO_2 can be allocated to the producing firm, to downstream users of the product, and to multiple financing entities. This affects comparability across institutions and is directly relevant for assessing portfolio decarbonization claims.

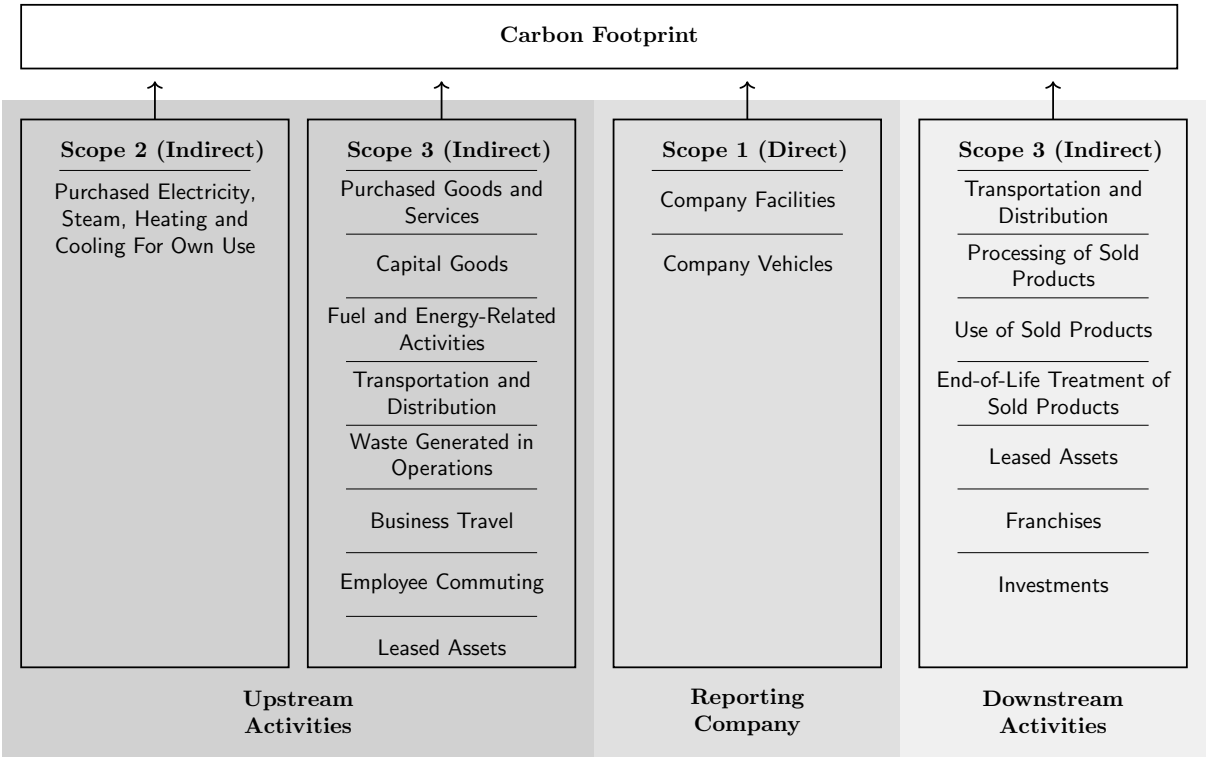


Figure A1: Scope 1, Scope 2, and Scope 3 emission categories along a company's value chain. Upstream categories capture inputs and suppliers, Scope 1 and Scope 2 reflect on-site combustion and purchased energy, and downstream categories capture distribution, product use, and end-of-life treatment. Financed emissions (Scope 3, Category 15) allocate a share of investee emissions to investors and lenders. Source: Greenhouse Gas Protocol (2004); State Street Global Advisors (2020); Authors.

Predicting Future Cash Flows

The OLS regressions reported here assess whether Relative Carbon Profitability (RCP) helps forecast next-year operating cash flows, following Ang et al. (2024). The dependent variable is next-year operating cash flow scaled by assets, $\text{CFO/Assets}_{i,t+1}$. We regress $\text{CFO/Assets}_{i,t+1}$ on current-period cash-flow performance and carbon-related measures. The estimating equation is

$$\begin{aligned}\text{CFO/Assets}_{i,t+1} = \alpha + \beta_1 \,\text{CFO/Assets}_{i,t} + \beta_2 \,\text{Emissions/Sales}_{i,t} + \beta_3 \,\text{RCP}_{i,t} \\ + \beta_4 \,\text{Sales/Assets}_{i,t} + \beta_5 \,\text{CP/Assets}_{i,t} + \gamma_j + u_{i,t},\end{aligned} \tag{1}$$

where γ_j are industry fixed effects, $\text{RCP}_{i,t}$ is the carbon-adjusted profitability measure, and $\text{CP/Assets}_{i,t}$ captures the emissions-implied cost (sometimes referred to as the emissions-implied charge on profits). $\text{Sales/Assets}_{i,t}$ is asset turnover. $\text{Emissions/Sales}_{i,t}$ is Scope 1 + 2 emissions scaled by sales, which is a standard emissions intensity metric. All standard errors are heteroskedasticity-robust and clustered at the firm level. We run the regressions both with the full RCP term and with its components separately to evaluate whether any predictive content comes through higher operating efficiency or through lower embedded carbon cost. The results are in Table A1.

Table A1: Predicting next-year CFO/Assets. The dependent variable is CFO/Assets_{t+1}. Reported are OLS coefficients with t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. All specifications include industry fixed effects and heteroskedasticity-robust standard errors clustered at the firm level. The sample is restricted to firms with a complete panel and non-missing CFO/Assets_{t+1}. Variables: Emissions/Sales is Scope 1+2 emissions scaled by sales; RCP is relative carbon profitability; Sales/Assets is sales scaled by total assets; CP/Assets is carbon profit scaled by assets.

Variable	(1)	(2)	(3)	(4)
CFO/Assets_t	0.7525***	0.7524***	0.7349***	0.7349***
	(83.28)	(83.27)	(81.42)	(81.45)
Emissions/Sales_t	0.0004			0.0001
	(1.14)			(0.24)
RCP_t		-0.0003		
		(-1.10)		
Sales/Assets_t			0.0092***	0.0092***
			(9.82)	(9.74)
CP/Assets_t			-0.0013***	-0.0013***
			(-4.46)	(-3.98)
Adj. R^2	0.5542	0.5542	0.5574	0.5574
N	27,040	27,040	27,040	27,040

Table A1 shows three main patterns. First, current-period cash-flow performance is the dominant predictor of next-year CFO/Assets, with coefficients around 0.73 to 0.75, which indicates strong persistence in operating profitability. Second, the conventional emissions intensity ratio Emissions/Sales is statistically insignificant once we control for lagged profitability, which suggests limited incremental forecasting power from raw emissions per unit of revenue. Third, when we decompose RCP, the asset-turnover component Sales/Assets is positive and significant, while the emissions-implied cost component CP/Assets is negative and significant. This points to weaker and less persistent cash-flow performance at firms whose revenue generation relies more heavily on carbon-intensive production.

Scope 3 Exposure Profiles

The panels illustrate how the sectoral distribution of portfolio emissions looks when attention is restricted to Scopes 1 and 2, and how this distribution changes once Scope 3 is incorporated. They highlight how value-chain emissions reshape which sectors appear most carbon intensive from an investor perspective. When only Scopes 1 and 2 are considered, exposure is concentrated in energy, utilities, and materials, while sectors such as financials, real estate, and professional services appear small. Once Scope 3 is incorporated, the apparent contribution of financials, healthcare, consumer discretionary, and professional services increases, and the energy sector's footprint expands as emissions from product use are captured. This comparison shows that value-chain emissions can materially affect how portfolio carbon exposure is allocated across industries, especially in sectors that otherwise appear low-risk under Scopes 1 and 2 alone.

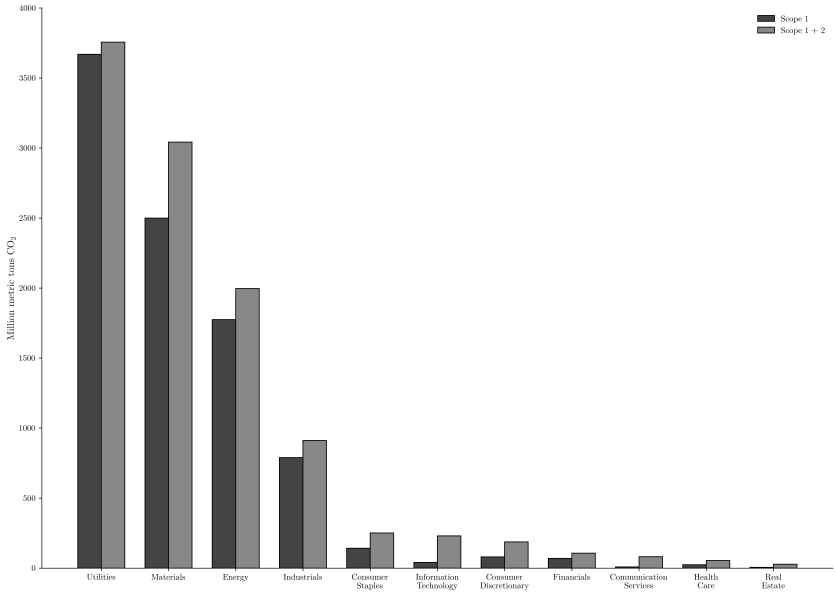


Figure A2: Sectoral distribution of portfolio emissions based on Scope 1 and 2 data. Dark bars show Scope 1 contributions, and light bars show Scope 2 contributions. Data sourced from MSCI ESG Research.

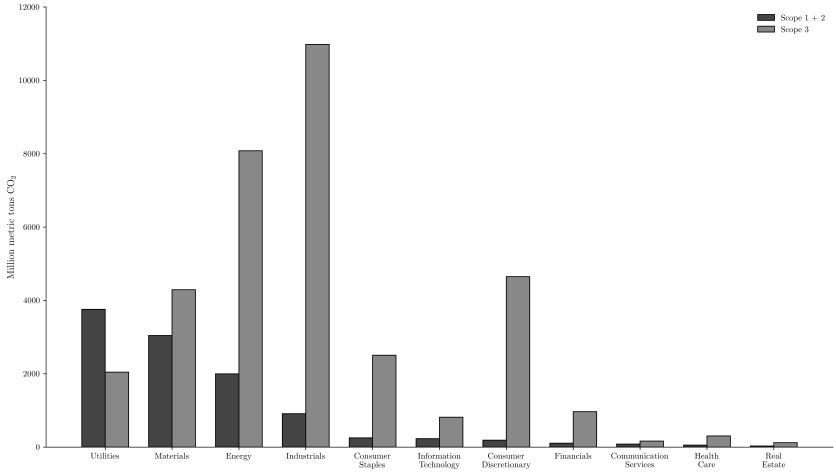


Figure A3: Sectoral distribution of portfolio emissions when Scope 1, Scope 2, and Scope 3 data are included. Dark bars correspond to Scope 1 + 2, and light bars to Scope 3. Data sourced from MSCI ESG Research.

Concentration of Scope 1 + 2 Emissions

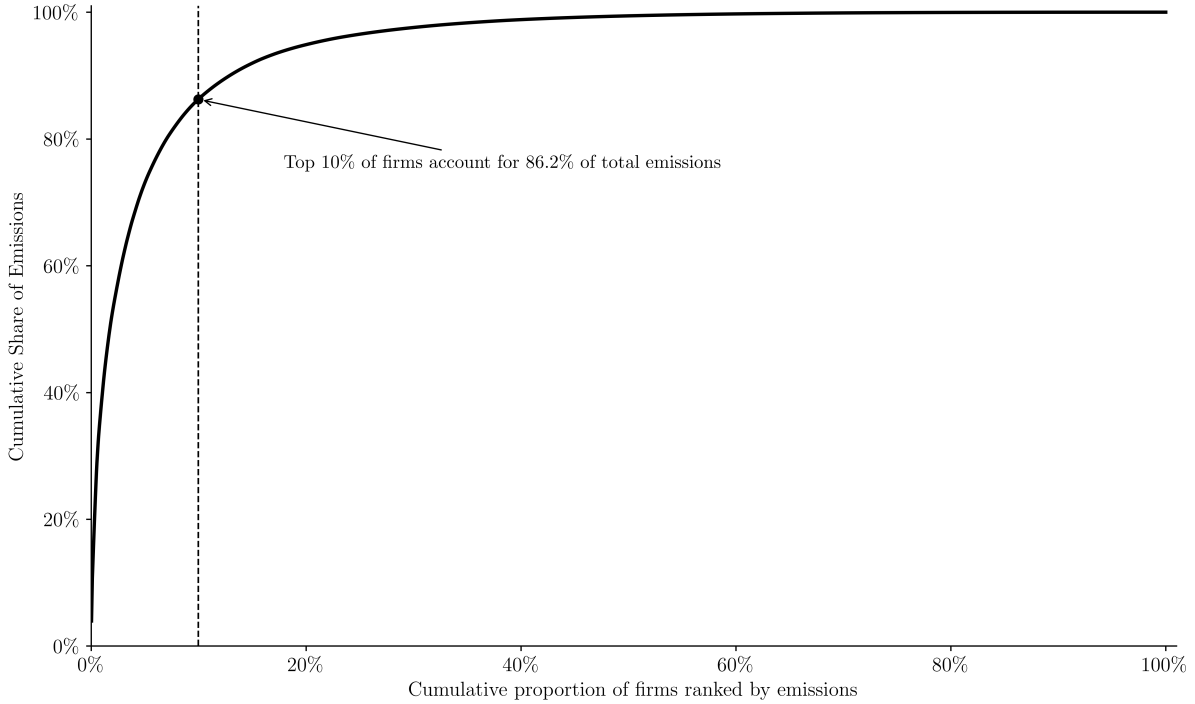


Figure A4: Cumulative concentration of Scope 1 + 2 emissions across firms in MSCI ACWI at year end 2023. The solid curve shows the cumulative share of total emissions against the cumulative proportion of firms ranked by average emissions. The dashed vertical line marks the 10 percent threshold among the largest emitters.

Geographic Concentration of Reported Emissions

The figure summarises the geographic distribution of reported Scope 1 and 2 emissions among the largest emitting economies in the MSCI ACWI universe. The figure compares total absolute emissions in Developed Markets and Emerging Markets for the eight largest emitters in each group, using snapshots from 2015, 2019, and 2023. In developed markets, reported emissions tend to stabilise or decline, which is consistent with higher deployment of low carbon technologies and gradual transitions toward more service-oriented production. In emerging markets, particularly large industrial economies such as China, total reported emissions remain higher and in several cases continue to rise. This pattern illustrates how aggregate decarbonisation progress differs across regions even within a global benchmark.

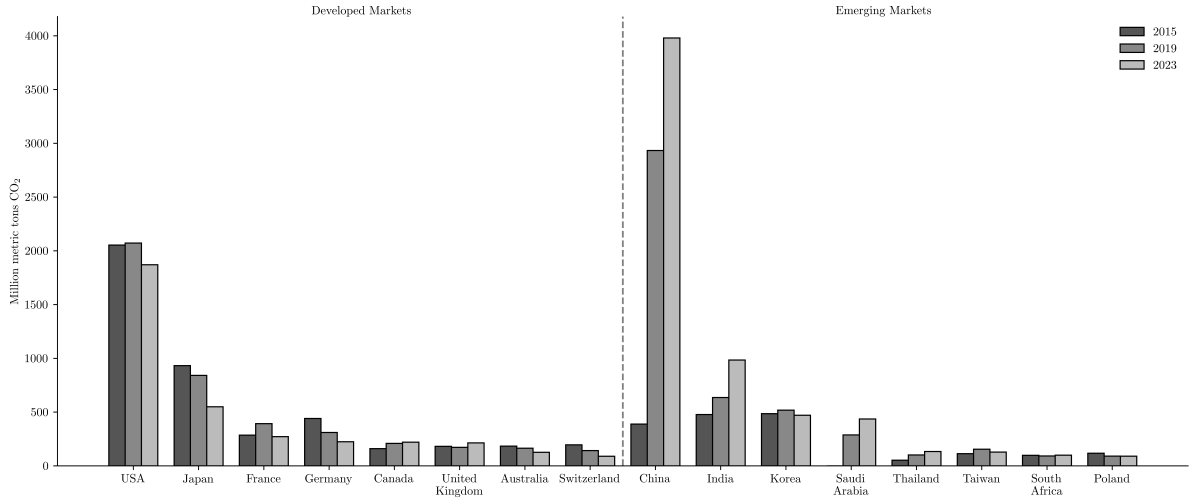


Figure A5: Comparison of total Scope 1 + 2 emissions (million t CO_2) in 2015, 2019, and 2023 for the eight largest emitters, split between Developed and Emerging Markets. Bars are shaded by year (dark: 2015, medium: 2019, light: 2023). Data sourced from MSCI ESG Research with classifications based on MSCI's Market Classification Framework.

Country-Level Performance Attribution Pure Exclusion

Table A2: Performance attribution analysis by country for Pure Exclusion portfolios at thresholds 75%, 90%, and 99% relative to the common benchmark. The table reports benchmark country weights and returns, portfolio weights and returns, and allocation, selection, and total effects. Benchmark country weights and returns are constant across panels. "Return" reflects the sector's return, while "Total" is the contribution to portfolio return computed as weight × return and summed across countries. "Allocation" reflects return from strategy reallocation vs. the benchmark, while "Selection" reflects return from stock performance within countries at matched weights.

	Benchmark			Portfolio PX 75%			Attribution PX 75%		
Country	Weight	Return	Total	Weight	Return	Total	Alloc.	Select.	Total
USA	55.52	20.07	11.39	56.26	20.83	12.01	0.15	0.43	0.58
Japan	8.37	12.61	1.10	9.36	12.50	1.22	0.13	−0.01	0.12
United Kingdom	4.80	11.39	0.58	5.75	10.43	0.64	0.11	−0.06	0.05
France	3.62	13.22	0.53	4.09	13.45	0.61	0.06	0.01	0.07
Switzerland	3.05	12.05	0.38	2.86	12.52	0.34	−0.02	0.01	−0.01
Canada	3.02	13.12	0.41	2.86	14.30	0.41	−0.02	0.03	0.01
Germany	3.02	12.87	0.43	3.05	13.00	0.42	0.00	0.00	0.01
Australia	2.55	12.49	0.36	2.57	12.11	0.35	0.00	−0.01	−0.01
Korea	1.77	13.19	0.28	1.36	12.34	0.20	−0.05	−0.01	−0.07
Taiwan	1.70	19.21	0.35	0.99	17.07	0.17	−0.14	−0.02	−0.16
China	1.61	17.50	0.30	1.22	18.97	0.26	−0.07	0.02	−0.05
				Portfolio PX 90%			Attribution PX 90%		
Country				Weight	Return	Total	Alloc.	Select.	Total
USA				56.63	20.15	11.68	0.22	0.05	0.27
Japan				8.79	12.69	1.15	0.05	0.01	0.06
United Kingdom				5.26	11.29	0.63	0.05	−0.01	0.05
France				3.95	13.03	0.57	0.04	−0.01	0.04
Switzerland				3.30	11.92	0.41	0.03	0.00	0.03
Canada				2.84	13.30	0.38	−0.02	0.01	−0.02
Germany				2.90	13.24	0.42	−0.02	0.01	0.00
Australia				2.49	12.32	0.35	−0.01	0.00	−0.01
Korea				1.40	14.14	0.23	−0.05	0.01	−0.04
Taiwan				1.01	15.81	0.17	−0.13	−0.03	−0.17
China				1.22	17.49	0.24	−0.07	0.00	−0.07
				Portfolio PX 99%			Attribution PX 99%		
Country				Weight	Return	Total	Alloc.	Select.	Total
USA				55.84	20.05	11.43	0.06	−0.01	0.05
Japan				8.68	12.58	1.13	0.04	0.00	0.04
United Kingdom				4.81	11.28	0.58	0.00	0.00	0.00
France				3.77	13.17	0.55	0.02	0.00	0.02
Switzerland				3.10	12.01	0.39	0.01	0.00	0.01
Canada				3.01	13.11	0.41	0.00	0.00	0.00
Germany				3.00	12.72	0.41	0.00	0.00	−0.01
Australia				2.62	12.39	0.37	0.01	0.00	0.01
Korea				1.77	13.31	0.29	0.00	0.00	0.00
Taiwan				1.74	19.26	0.36	0.01	0.00	0.01
China				1.33	16.48	0.25	−0.05	−0.01	−0.06

Country-Level Performance Attribution Best-In-Class

Table A3: Performance attribution analysis by country for Best-In-Class portfolios at thresholds 75%, 90%, and 99% relative to the common benchmark. The table reports benchmark country weights and returns, portfolio weights and returns, and allocation, selection, and total effects. Benchmark country weights and returns are constant across panels. "Return" reflects the sector's return, while "Total" is the contribution to portfolio return computed as weight × return and summed across countries. "Allocation" reflects return from strategy reallocation vs. the benchmark, while "Selection" reflects return from stock performance within countries at matched weights.

	Benchmark			Portfolio BIC 75%			Attribution BIC 75%		
Country	Weight	Return	Total	Weight	Return	Total	Alloc.	Select.	Total
USA	55.52	20.07	11.39	55.97	20.33	11.57	0.09	0.15	0.23
Japan	8.37	12.61	1.10	9.17	12.69	1.21	0.10	0.01	0.11
United Kingdom	4.80	11.39	0.58	5.39	10.87	0.63	0.07	−0.03	0.04
France	3.62	13.22	0.53	3.47	13.24	0.51	−0.02	0.00	−0.02
Switzerland	3.05	12.05	0.38	3.25	12.67	0.41	0.02	0.02	0.04
Canada	3.02	13.12	0.41	3.06	14.24	0.44	0.00	0.03	0.04
Germany	3.02	12.87	0.43	2.66	12.80	0.37	−0.05	0.00	−0.05
Australia	2.55	12.49	0.36	2.27	12.16	0.32	−0.03	−0.01	−0.04
Korea	1.77	13.19	0.28	1.68	12.40	0.24	−0.01	−0.01	−0.03
Taiwan	1.70	19.21	0.35	1.47	18.39	0.31	−0.05	−0.01	−0.06
China	1.61	17.50	0.30	1.71	18.88	0.35	0.02	0.02	0.04
				Portfolio BIC 90%			Attribution BIC 90%		
Country				Weight	Return	Total	Alloc.	Select.	Total
USA				56.31	20.14	11.58	0.16	0.04	0.20
Japan				8.97	12.77	1.19	0.08	0.02	0.09
United Kingdom				4.87	11.29	0.58	0.01	0.00	0.00
France				3.61	13.09	0.53	0.00	0.00	−0.01
Switzerland				3.37	11.61	0.42	0.04	−0.01	0.02
Canada				2.67	13.42	0.37	−0.05	0.01	−0.04
Germany				2.69	13.29	0.39	−0.04	0.01	−0.03
Australia				2.37	12.18	0.34	−0.02	−0.01	−0.03
Korea				1.69	13.66	0.26	−0.01	0.01	0.00
Taiwan				1.50	17.68	0.31	−0.04	−0.02	−0.06
China				1.61	17.92	0.33	0.00	0.01	0.01
				Portfolio BIC 99%			Attribution BIC 99%		
Country				Weight	Return	Total	Alloc.	Select.	Total
USA				55.95	20.05	11.46	0.09	−0.01	0.08
Japan				8.60	12.59	1.13	0.03	0.00	0.03
United Kingdom				4.75	11.29	0.57	−0.01	0.00	−0.01
France				3.73	13.16	0.54	0.01	0.00	0.01
Switzerland				3.11	11.88	0.38	0.01	−0.01	0.00
Canada				3.01	13.14	0.40	0.00	0.00	0.00
Germany				2.98	12.73	0.41	−0.01	0.00	−0.01
Australia				2.59	12.38	0.37	0.01	0.00	0.00
Korea				1.82	13.50	0.30	0.01	0.01	0.01
Taiwan				1.75	19.13	0.37	0.01	0.00	0.01
China				1.36	16.65	0.26	−0.04	−0.01	−0.06

Performance metrics – CI Pure Exclusion (ACWI)

Table A4: Summary statistics for the Pure Exclusion (PX) strategy. The table reports average values over the full sample period for portfolio performance, portfolio characteristics, tracking analysis, carbon metrics, and factor exposures. Results are reported for the benchmark and for PX portfolios constructed at the 99%, 90%, and 75% CI thresholds. Definitions of selected portfolio metrics are provided in Appendix A. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Significance levels correspond to H_0: $\beta = 0$ for all factors, except for MKT–RF where H_0: $\beta = 1$.

Metric	**Benchmark**	**PX 99%**	**PX 90%**	**PX 75%**
Return and Risk				
Total return (%)	17.49	17.48	17.94	18.84
Total risk (%)	14.29	14.31	14.26	14.52
Return/risk	1.224	1.222	1.258	1.298
Sharpe ratio	1.207	1.205	1.241	1.281
Max drawdown (%)	-20.36	-20.13	-22.07	-22.58
Portfolio Characteristics				
Average number of positions	2047	1748	1465	1199
Effective number of positions	252	230	196	160
Top-ten weight (%)	13.67	14.45	15.93	18.49
Turnover (%)	10.94	10.93	11.76	14.41
Tracking Analysis				
Active return (%)	–	-0.04	0.04	0.38
Tracking error (%)	–	0.32	0.56	1.47
Information ratio	–	-0.12	0.08	0.26
Historical beta	–	1.00	1.00	1.04
Carbon Metrics				
WACI change (%)	–	3.05	-27.46	-62.18
CF change (%)	–	-6.89	-41.29	-60.06
CI change (%)	–	-3.75	-39.99	-61.03
Factor Exposures				
Alpha	0.005***	0.005***	0.005***	0.006***
MKT-RF	0.977**	0.978*	0.968**	0.969**
SMB	-0.127***	-0.140***	-0.169***	-0.214***
HML	-0.085**	-0.075*	-0.101**	-0.081**
RMW	0.037	0.044	0.052	0.024
CMA	0.096*	0.103*	0.053	-0.056
WML	-0.035**	-0.033**	-0.038**	-0.034
R^2	0.992	0.992	0.991	0.985
Obs.	124	124	124	124

Performance metrics – CI Best-in-Class (ACWI)

Table A5: Summary statistics for the Best-In-Class (BIC) strategy. The table reports average values over the full sample period for portfolio performance, portfolio characteristics, tracking analysis, carbon metrics, and factor exposures. Results are reported for the benchmark and for BIC portfolios constructed at the 99%, 90%, and 75% CI thresholds. Definitions of selected portfolio metrics are provided in Appendix A. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels. Significance levels correspond to H_0: $\beta = 0$ for all factors, except for MKT–RF where H_0: $\beta = 1$.

Metric	**Benchmark**	**BIC 99%**	**BIC 90%**	**BIC 75%**
Return and Risk				
Total return (%)	17.49	17.43	17.54	17.83
Total risk (%)	14.29	14.24	14.27	14.61
Return/risk	1.224	1.223	1.229	1.220
Sharpe ratio	1.207	1.207	1.212	1.204
Max drawdown (%)	-20.36	-20.04	-20.57	-21.97
Portfolio Characteristics				
Average number of positions	2047	1749	1476	1217
Effective number of positions	252	233	209	176
Top-ten weight (%)	13.67	14.33	15.19	17.29
Turnover (%)	10.94	11.18	12.89	16.44
Tracking Analysis				
Active return (%)	–	-0.03	0.10	0.14
Tracking error (%)	–	0.31	0.53	0.81
Information ratio	–	-0.11	0.18	0.17
Historical beta	–	1.00	0.99	1.01
Carbon Metrics				
WACI change (%)	–	2.10	-30.42	-58.57
CF change (%)	–	-7.58	-42.34	-56.26
CI change (%)	–	-5.12	-44.92	-61.08
Factor Exposures				
Alpha	0.005***	0.005***	0.005***	0.005***
MKT-RF	0.977**	0.975**	0.978*	0.999
SMB	-0.127***	-0.135***	-0.120***	-0.095**
HML	-0.085**	-0.074*	-0.059	-0.077*
RMW	0.037	0.053	0.069	0.036
CMA	0.096*	0.109*	0.093	0.053
WML	-0.035**	-0.032*	-0.022	-0.008
R^2	0.992	0.992	0.991	0.990
Obs.	124	124	124	124

Appendix C: How Stale Is "Historical" Carbon Data?

At any portfolio date t, institutional investors usually observe emissions that issuers reported for fiscal year $t-1$ and, on occasion, for $t-2$. The practical question is whether these delayed figures are sufficiently informative for portfolio decisions. Bixby et al. (2022) shows that the median delay from fiscal year end to public release is just over one calendar year, where only a small minority of firms publish data within twelve months. Figure A6 summarises this timing. At time t, the portfolio is formed or assessed using emissions from $t-1$, while actual emissions for year t become observable only at $t+1$. In other words, past data are the only firm reference when decisions are made.

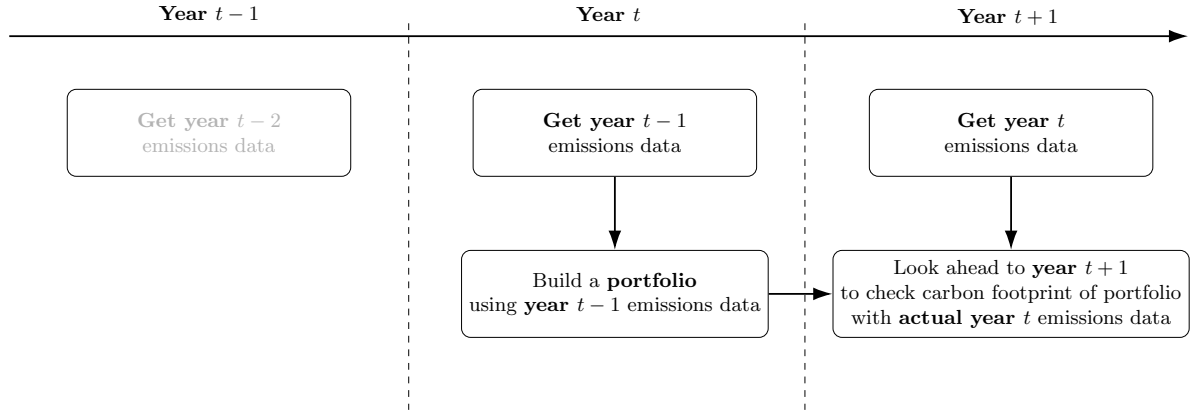
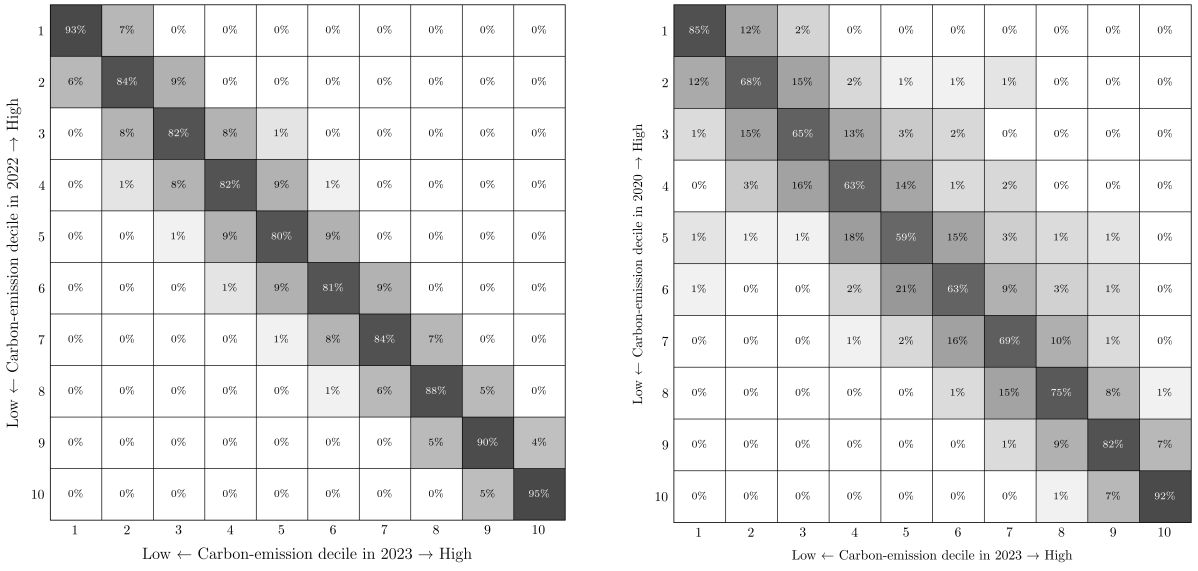


Figure A6: Stylised availability timeline. At portfolio date t the most recent observable emissions refer to fiscal year $t-1$. Emissions from fiscal year t become public at $t+1$. Source: Bixby et al. (2022); Authors.

Building on this timeline, we evaluate the loss of information by sorting all listed firms with available emissions data into deciles according to their total Scope $1+2$ emissions. We then construct transition matrices to quantify the persistence of firms' emission rankings, shown in Figure A7.



(a) One-year

(b) Three-year

Figure A7: Carbon transition matrices. Rows denote emissions deciles in the initial year, and columns denote emissions deciles in the final year. Entries report the fraction of firms transitioning between deciles. Panel (a) shows one year transitions (2022–2023), while Panel (b) shows three year sector adjusted transitions (2020–2023). Data sourced from MSCI ESG Research.

This strong diagonal pattern indicates that high emitting firms tend to stay high emitters, and low emitters tend to stay low emitters, both in the short and longer horizon. However, despite the high rank persistence, rank stability alone does not guarantee accurate estimates of portfolio level emissions. Bixby et al. (2022) shows that when portfolios are formed at time t using historical data and held for twelve months, the realised footprint, calculated after disclosures for year t are released, differs on average by about one percent from the ex ante estimate for the MSCI World universe. For a low carbon portfolio, the gap is around four percent. These findings suggest that diversification offsets most firm specific measurement errors. Large outliers do occur, often linked to mergers that bring in emission intensive subsidiaries or to retrospective model revisions by data vendors, but such cases are rare and typically diluted at the portfolio level.

The past decade was also unusually stable in emissions, yet a sharp macro decarbonisation would make historical data overstate current financed emissions, introducing a conservative bias. The pandemic year 2020 illustrates this point, when energy demand collapsed and global CO_2 fell by about six percent, meaning that 2019 based footprints overstated ex post emissions. However, in regulatory and fiduciary contexts, it remains safer to overstate than to understate financed emissions.

Data quality also matters. Bixby et al. (2022) notes that fewer than two thirds of large capitalisation issuers obtain assurance on reported ESG metrics, and only a small fraction use their statutory auditor. Scope 1 + 2 data remain the most reliable subset, with cross vendor correlation above 0.9, whereas Scope 3 estimates remain heterogeneous.

Overall, lagged historical carbon data provide a robust basis for short horizon climate metrics. The burden of proof therefore rests on forward looking models, where they must demonstrate meaningful improvement over simply using last year's disclosures. Until such evidence appears, the practical default is to rely on the most recent verified numbers and to track forecast error empirically.

Appendix D: Regional Portfolio Composition

Sector Weights within Regional Benchmarks

Table A6: Average sector weights in percent for regional benchmarks (BM) and for portfolios constructed using carbon intensity (CI) and relative carbon profitability (RCP) as screening criteria under the pure exclusion strategy. The table is organised in three panels that correspond to Europe, North America, and Pacific. Rows list the eleven GICS sectors. Columns report BM together with CI 99%, CI 90%, CI 75% and RCP 99%, RCP 90%, RCP 75%. Weights are time averages over the sample and reflect the same benchmark, constraints, and rebalancing choices as in the baseline specification. Within each panel, sector weights in each column sum to 100% subject to minor rounding differences.

Sector	BM	CI 99%	CI 90%	CI 75%	RCP 99%	RCP 90%	RCP 75%
Europe							
Energy	6.24	6.29	5.02	0.10	6.29	5.91	5.66
Materials	6.78	5.85	2.34	0.92	6.56	5.95	6.16
Industrials	13.49	13.69	14.69	16.15	13.40	14.58	17.41
Consumer Discretionary	10.03	9.91	10.81	12.94	9.67	10.28	11.99
Consumer Staples	13.96	14.48	16.05	12.50	14.30	10.97	10.41
Health Care	13.29	13.48	14.94	16.10	13.33	13.33	15.27
Financials	19.91	20.29	22.49	27.32	20.12	22.40	17.50
Information Technology	5.50	5.53	6.13	6.73	5.36	5.51	6.56
Communication Services	4.92	4.99	5.52	6.45	4.98	4.91	3.86
Utilities	4.74	4.34	0.97	0.02	4.92	5.07	4.46
Real Estate	1.16	1.14	1.04	0.78	1.08	1.09	0.73
North America							
Energy	7.51	7.62	4.03	0.57	7.63	7.84	7.44
Materials	2.54	2.41	1.27	0.54	2.44	2.37	2.59
Industrials	8.41	8.39	7.57	6.35	8.37	8.06	8.54
Consumer Discretionary	11.13	11.29	12.14	12.20	10.99	11.52	13.20
Consumer Staples	8.58	8.84	9.80	7.83	8.63	8.73	7.40
Health Care	12.58	12.68	14.07	16.59	12.61	9.90	6.34
Financials	15.82	16.00	17.06	19.62	15.99	16.52	19.63
Information Technology	22.48	22.84	25.25	28.47	22.32	23.21	23.96
Communication Services	4.95	5.00	5.54	6.12	5.00	5.55	5.02
Utilities	3.25	2.18	0.48	0.01	3.26	3.59	3.02
Real Estate	2.75	2.75	2.80	1.70	2.75	2.70	2.85
Pacific							
Energy	1.32	1.21	0.60	0.28	1.22	1.02	0.83
Materials	7.54	7.43	1.93	0.15	7.61	7.47	7.77
Industrials	16.28	16.45	16.87	15.12	15.86	16.95	19.50
Consumer Discretionary	14.84	15.17	16.63	17.58	15.00	14.43	13.64
Consumer Staples	6.42	6.46	7.07	5.49	6.45	5.93	5.40
Health Care	7.09	7.25	8.02	8.75	7.07	5.48	3.67
Financials	24.47	24.83	27.30	31.87	24.77	26.89	29.27
Information Technology	8.46	8.52	9.32	9.17	8.47	7.89	8.13
Communication Services	4.97	5.02	5.54	6.51	5.02	5.14	4.64
Utilities	2.67	1.86	0.62	0.16	2.70	2.56	2.11
Real Estate	5.95	5.82	6.11	4.92	5.81	6.23	5.04

Country Weights within Regional Benchmarks

Table A7: Average country weights in percent for regional benchmarks (BM) and for portfolios constructed using carbon intensity (CI) and relative carbon profitability (RCP) as screening criteria under the pure exclusion strategy. The table is organised in three panels that correspond to Europe, North America, and Pacific. For each panel the rows contain the countries with the largest benchmark shares in that regional index as determined by average benchmark weight. Within each panel rows are ordered by the benchmark weight in descending order. Columns report BM together with CI 99%, CI 90%, CI 75% and RCP 99%, RCP 90%, RCP 75%. Weights are time averages over the sample and are expressed in percent. Within each panel, country weights in each column sum to 100% subject to minor rounding differences.

Country	**BM**	**CI 99%**	**CI 90%**	**CI 75%**	**RCP 99%**	**RCP 90%**	**RCP 75%**
Europe							
United Kingdom	24.68	24.98	25.13	26.01	24.71	26.98	24.20
France	18.84	19.34	19.38	20.44	19.44	20.33	21.55
Switzerland	15.95	16.08	17.81	15.90	16.22	13.72	14.94
Germany	15.52	15.37	15.46	14.79	15.60	14.82	15.47
Spain	5.26	5.42	4.71	5.33	5.38	5.88	5.34
Netherlands	4.44	4.23	4.66	5.12	4.22	4.41	4.64
Sweden	4.05	3.81	4.21	4.93	3.74	4.15	4.95
Italy	3.67	3.69	2.37	2.59	3.66	3.35	2.67
Denmark	1.94	1.64	1.58	1.41	1.50	1.48	1.71
Finland	1.54	1.48	1.40	1.38	1.61	1.64	1.81
Belgium	1.38	1.24	1.23	1.00	1.20	1.06	0.71
North America							
USA	94.73	94.81	95.72	95.57	94.78	94.79	94.62
Canada	5.27	5.19	4.28	4.43	5.22	5.21	5.38
Pacific							
Japan	67.37	68.32	70.75	71.23	67.97	69.38	70.26
Australia	20.42	20.29	17.86	18.10	20.52	19.30	19.81
Hong Kong	7.96	7.18	7.07	6.18	7.44	7.07	5.70
Singapore	3.74	3.74	3.84	4.01	3.60	3.72	3.64
New Zealand	0.53	0.48	0.48	0.48	0.48	0.53	0.59

Appendix E: MSCI Scope 1 and 2 Estimation Framework

MSCI ESG Research estimates Scope 1 + 2 emissions using a three-step framework.[1] First, the production model applies to power-generation companies only, providing direct emissions estimates based on consumption and fuel mix across coal, liquid fuels, natural gas, nuclear, and renewables. Second, the company-specific intensity model serves as an emissions-intensity proxy. MSCI derives historical intensities from reported issuer emissions and revenue data, then applies current revenue to impute missing values. This approach uses firm-specific information whenever available and preserves time-series continuity for companies with partial disclosure histories. Third, the industry-segment intensity model provides an industry-specific intensity proxy by averaging firm-level intensities within each segment and multiplying by segment revenues. Firms with zero or undisclosed revenues receive the segment average intensity to preserve comparability across issuers and time.

To reconcile partial disclosures and structural breaks, MSCI applies a set of logical rules that blend reported and estimated Scope 1 and Scope 2 data. These rules select the most appropriate model when corporate actions such as mergers, spin-offs, or divestments make historical data non-representative. Scope 1 and 2 estimates are updated continuously on a rolling basis following companies' annual filings and are typically recalculated biweekly to incorporate the latest disclosures.

Figure A8 illustrates how the three estimation modules have contributed to Scope 1 + 2 coverage over time in our sample. In the left panel, the company-specific intensity model (E.CSI) accounts for the majority of Scope 1 imputations in the early years, representing more than 80% of all estimates by 2017. This likely reflects the availability of historical firm-level emissions and revenue data even when current disclosures were incomplete.

From around 2018, the production-based approach (E.PROD) gradually increases its share as production data become more accessible and more power-generation firms report fuel-specific metrics. The segment-level intensity method (E.SEGMT) also becomes more important in cases where revenue disclosures are limited or delayed. The right panel shows a similar progression for Scope 2 coverage. These shifts are relevant for interpreting early-year data because reliance on different estimation methods affects both measurement error and comparability across firms.

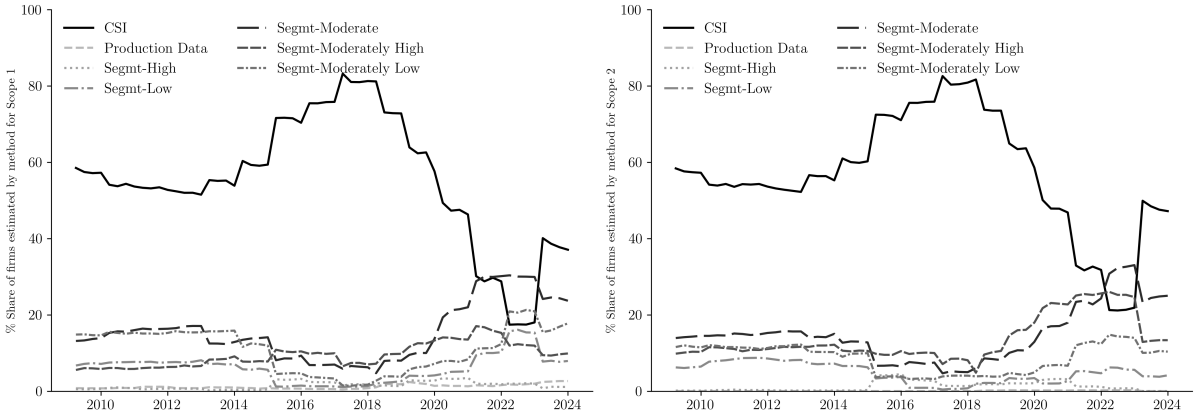


Figure A8: Share of firms estimated by each MSCI Scope 1 + 2 estimation module, 2009–2023. Left: Scope 1 methods; Right: Scope 2 methods. Data sourced from MSCI ESG Research.

[1] Details on the methodology can be found in the technical documentation by MSCI ESG Research, available at: `https://www.msci.com/documents/1296102/39141520/MSCI+Greenhouse+Gas+Emissions+Methodologies.pdf`.