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Review

The performance of low-carbon equity funds

Kevin Birk [a,*], Martin Rohleder [b], René Weh [c], Marco Wilkens [b]

[a] University of Augsburg, Faculty of Business Administration and Economics, Chair of Finance and Banking, Universitaetsstr. 16, 86159 Augsburg, Germany
[b] University of Augsburg, Faculty of Business Administration and Economics, Chair of Finance and Banking, Germany
[c] Eurex Clearing AG, Deutsche Börse Group, Treasury Manager, Mergenthalerallee 61, 65760 Eschborn, Germany

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ABSTRACT

This study examines the performance of low-carbon equity funds by gaining a better understanding of what drove past performance, what opportunity costs arose from higher idiosyncratic risks, and which components would shape future expectations. Low-carbon funds outperformed medium- and high-carbon funds under traditional factor models, but this advantage declined after incorporating carbon-related factors and fund characteristics. Adjusting for the opportunity costs of idiosyncratic risk particularly weakened low-carbon fund performance. Considering factor premia, exposures, characteristics, and diversification costs, investors should expect lower returns relative to a passive market-wide benchmark and roughly comparable outcomes across low-, medium-, and high-carbon funds.

1. Introduction

In recent years, sustainable investments have surged, both in capital inflows and in the number of mutual funds launched. Since the Paris Agreement in December 2015, low-carbon investments have attracted investors seeking either to support climate change mitigation or to respond to social, political, and regulatory pressures. Although many studies have analyzed the performance of sustainable funds—typically emphasizing environmental, social, and governance (ESG) factors (e.g., Friede et al., 2015)—few have specifically examined low-carbon funds or the components driving their performance (e.g., Guo et al., 2022; Ibikunle & Steffen, 2017).

To address this gap, we systematically evaluate the performance of low-carbon equity funds through three key questions relevant to current and prospective investors:

- How have low-, medium-, and high-carbon funds performed in recent years, and what factors and characteristics explain this performance?
- What opportunity costs arise from the higher idiosyncratic risk of low-carbon funds?
- Which aspects of past financial performance can inform future expectations?

Comparing low- and high-carbon funds provides valuable insight into the financial consequences of climate-related investment choices. Medium-carbon funds serve as a conventional benchmark, while low-carbon funds are structured to align with climate objectives and sustainability goals. Contrasting them with high-carbon funds helps identify whether observed performance differences stem from carbon-related risk exposures, factor loadings, or managerial skill, offering a clearer picture of the performance landscape relevant to both investors and regulators.

To address our first research question on ex post fund performance, we analyze 1827 actively managed U.S. domestic equity funds from January 2017 to December 2024. We first apply traditional factor models (i.e., capital asset pricing model (CAPM) (Lintner, 1965; Mossin, 1966; Sharpe, 1964) and the Fama and French (2015) five-factor model combined with Carhart (1997)) yielding a six-factor (FF/Carhart) model. Using monthly excess returns, we estimate risk-adjusted returns ("alpha"). Based on these models, low-carbon funds significantly outperformed medium- and high-carbon funds during the sample period, consistent with prior studies (e.g., Kuang & Liang, 2022; Reboredo &

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* Corresponding author.
E-mail addresses: kevin.birk@wiwi.uni-augsburg.de (K. Birk), martin.rohleder@wiwi.uni-augsburg.de (M. Rohleder), rene.weh@deutsche-boerse.com (R. Weh), marco.wilkens@wiwi.uni-augsburg.de (M. Wilkens).

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Otero González, 2022; Soler-Domínguez et al., 2021). However, all fund categories underperformed passive, market-wide benchmarks on average.

Next, we incorporate two carbon-related factors into the six-factor model: an industry-independent carbon intensity (CI) factor reflecting absolute exclusion strategies, and an industry-adjusted factor capturing best-in-class approaches. These additions create seven-factor brown–-green types I (BMG I) and II (BMG II—eight-factor) models consistent with the expanding carbon-related asset pricing literature (e.g., Görgen et al., 2020; Hsu et al., 2023; Pástor et al., 2021). Even with these enhancements, low-carbon funds continue to outperform medium- and high-carbon funds, though by a smaller margin than under traditional models.

Finally, we evaluate the role of fund characteristics using multivariate panel regressions. In line with existing research, fund activity and expenses are negatively related to risk-adjusted performance, while net flows and concentration in top ten holdings are positively related. Controlling these characteristics further narrows the outperformance of low-carbon funds. Yet their remaining advantage suggests systematic differences in managerial skill among low-, medium-, and high-carbon funds—differences not explained solely by the strong performance of low-carbon stocks, lower trading activity, or higher concentration in leading assets.

Our second research question addresses the opportunity costs of idiosyncratic risk, recognizing that concentrated investment in low-carbon stocks narrows the investable universe and limits diversification (e.g., Ceccarelli et al., 2024). This assumes investors are not further diversified across multiple funds or portfolios. We therefore estimate opportunity costs for investors lacking additional diversification—a realistic scenario, especially among sustainable investors.

We find that both low- and high-carbon funds exhibit significantly higher idiosyncratic risk than medium-carbon funds across all factor models, with low-carbon funds showing the highest levels. This pattern is most pronounced at the extremes, particularly in the four lowest low-carbon deciles and the two highest high-carbon deciles. After adjusting for the opportunity costs of idiosyncratic risk, the financial performance of all funds declines substantially, as they remain less diversified than passive, market-wide benchmarks. The effect is strongest for low-carbon funds due to their elevated idiosyncratic risk.

Finally, our third question explores which aspects of low-carbon fund performance may inform future expectations. Rather than relying solely on ex post returns, investors should consider expected factor premia and fund-specific factor loadings. Regarding carbon-related factors, our results show that low-carbon funds load significantly negatively on the value factor high-minus-low (HML), the profitability factor robust-minus-weak (RMW), and the investment factor conservative-minus-aggressive (CMA), while high-carbon funds load positively. This implies that low-carbon funds are likely to underperform during periods when these factors yield positive premia.

Pástor et al. (2021) suggest a negative "greenium" for low-carbon stocks, as they provide nonmonetary utility to green investors, and a positive "carbon risk premium" for high-carbon stocks due to their greater sensitivity to unexpected changes in the pace of economic transition. Consequently, investors can, ceteris paribus, expect lower future returns from low-carbon funds than from medium- or high-carbon funds, even though historical results show the opposite.

Because the funds exhibit negative alphas, investors should generally anticipate lower performance than a passive market-wide benchmark with a comparable style. Performance differences will also depend on classical fund characteristics such as activity and size. Assuming these characteristics persist, average low-carbon funds may still perform slightly better than medium- or high-carbon funds, ceteris paribus.

Finally, investors should be aware of the opportunity costs associated with idiosyncratic risk arising from lower diversification and greater sector concentration relative to passive benchmarks. These effects are especially pronounced for low-carbon funds, which typically hold fewer securities and thus face higher diversification-related costs.

2. Literature review and contribution

Previous research has examined performance differences between sustainable and conventional funds, but most studies rely on traditional risk factor models. These analyses typically begin by defining sustainability, often using socially responsible investment (SRI) indicators or an ESG-based framework. Compared with broader ESG or SRI funds, low-carbon funds show similar performance patterns but differ in their exposure to carbon-specific factors and idiosyncratic risks. This distinction highlights that carbon-focused strategies may impose unique diversification costs relative to other sustainable investment approaches. As climate change has become a top investor concern (Macquarie, 2021), reflected in major capital inflows to low-carbon funds (e.g., Ceccarelli et al., 2024), the literature has increasingly focused on carbon-oriented funds—a key topic of this study.

Ibikunle and Steffen (2017) assess the performance of European green, conventional, and black (fossil energy) funds using the Carhart (1997) four-factor model. They find that green funds achieve risk-adjusted returns comparable to black funds but underperform conventional ones. Similarly, Guo et al. (2022) report no significant differences between fossil fuel and non-fossil fuel funds. In contrast, Soler-Domínguez et al. (2021) show stronger results for socially responsible funds with lower exposure to carbon-intensive and fossil fuel industries. Reboredo and Otero González (2022) find that funds with lower carbon transition risk earn higher risk-adjusted returns, while Kuang and Liang (2022) document a positive relationship between effective carbon risk management and future risk-adjusted performance.

Our study builds on prior research but extends the analysis of carbon-related fund investments by systematically decomposing the returns of low-, medium-, and high-carbon funds into their major performance components and examining their idiosyncratic risks. This approach identifies the key drivers of observed performance differences and clarifies the implications of investors' decisions to allocate capital to low- or high-carbon funds. By also assessing the potential persistence of these components, we offer ex ante insights with meaningful implications for investment strategy.

A central component is the distinct performance of the assets held within each fund. Although this may seem self-evident, it is critical to understanding overall fund outcomes. Traditional factor models such as the CAPM, the Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model account for this element by attributing part of the performance to investors' chosen factor exposures. However, the influence of sustainability on equity returns is often overlooked. The literature points to a "greenium" (i.e., a premium paid for the nonmonetary utility of holding low-carbon assets) and a compensating carbon risk premium for high-carbon assets (e.g., Pástor et al., 2021).

Performance disparities among stocks with different carbon exposures are well documented. Bolton and Kacperczyk (2021) found that carbon-intensive U.S. firms outperform peers beyond what known risk factors explain, a pattern confirmed in their global study (Bolton & Kacperczyk, 2023). Conversely, Bauer et al. (2022) showed that firms with lower carbon emissions outperform across G7 markets, while Pástor et al. (2022) reported recent gains for green U.S. stocks, driven by a demand surge linked to growing environmental awareness. Although evidence on whether low- or high-carbon stocks perform better remains mixed, the divergence in realized returns is clear. These variations likely contribute directly to the performance differences observed between low- and high-carbon funds. Because investors consciously select among these funds, the resulting performance linked to carbon exposure can be attributed to their investment choices.

Several studies have attempted to account for return variations between sustainable and conventional stocks by adding or substituting sustainable indices for the market portfolio (e.g., Climent & Soriano, 2011; Renneboog et al., 2008; Silva & Cortez, 2016). However, many researchers now advocate explicitly incorporating sustainability factors into standard asset pricing models. Görgen et al. (2020), for instance, introduced a carbon risk factor–mimicking portfolio that effectively explains systematic return variation. Hübel and Scholz (2020) constructed ESG risk factors that substantially increase the explanatory power of conventional models. Pástor et al. (2021) proposed an equilibrium framework in which an ESG taste factor and the market portfolio jointly determine asset prices, while Pedersen et al. (2021) extended the CAPM to include ESG-adjusted returns.

Zerbib (2022) developed a sustainability-adjusted CAPM illustrating how exclusionary screening and ESG integration affect asset prices. Avramov et al. (2022) analyzed the pricing implications of ESG uncertainty. Hsu et al. (2023) constructed a zero-investment portfolio that is long in high-toxic and short in low-toxic emission intensity, revealing a pollution premium not explained by known risk factors. Dobrick et al. (2025) tested whether ESG-based factors satisfy the criteria for risk factors in multifactor models. Using data from multiple providers (i.e., ASSET4, LSEG Refinitiv, and Moody's Vigeo Eiris) and extending Fama–French and Carhart frameworks with ESG variables, they show that these constructed factors capture common return variation over time, supporting the integration of ESG elements into standard asset pricing models.

Although the optimal factor specification remains inconclusive, the need to include such variables for accurate performance decomposition is clear. This study contributes to the literature by extending the Fama and French (2015) five-factor model, augmented with the Carhart (1997) momentum factor, through the integration of carbon-based factors. In doing so, we test whether factor-mimicking portfolios enhance the model's explanatory power in capturing return variation among low-, medium-, and high-carbon funds, providing a more precise framework for analyzing factor-driven performance.

After assessing the contribution of factor exposures to fund returns, we turn to additional components commonly examined in the mutual fund literature: fund characteristics and managerial skill. These elements may differ across low-, medium-, and high-carbon funds. Prior studies frequently include fund characteristics as controls in regressions to isolate manager-driven performance—a strategy also applied here.

Several characteristics are well known to affect performance. Indro et al. (1999), Berk and Green (2004), Chen et al. (2004), Yan (2008), Pástor et al. (2015), and Evans et al. (2023) all reported a negative relationship between fund size and performance, often described as diseconomies of scale. Dahlquist et al. (2000) also found that larger funds tend to underperform and that higher-cost funds yield weaker results, confirming earlier evidence from Carhart (1997), Gil-Bazo and Ruiz-Verdú (2009), and Vidal et al. (2015). Conversely, they showed that actively managed funds outperform passive ones. Cremers and Petajisto (2009) similarly documented superior results for funds with higher active share, which measures the portfolio's deviation from its benchmark. In contrast, Carhart (1997), Edelen et al. (2013), and Champagne et al. (2018) found that higher turnover—another indicator of activity—tends to reduce performance. Likewise, Edelen (1999), Alexander et al. (2007), Fulkerson and Riley (2017), and Rohleder et al. (2018) identified a negative impact of fund flows, particularly when motivated by liquidity needs.

Because low- and high-carbon funds may differ in their characteristics, these differences can lead to variations in performance. Our analysis explicitly examines how such characteristics influence performance in low- and high-carbon funds while estimating the returns attributable to characteristics-driven and manager-driven components.

In the second part of this paper, we extend the performance analysis to include the idiosyncratic risks of funds, as low-carbon funds may face diversification challenges by limiting their holdings primarily to low-carbon stocks rather than the full equity universe. This restriction can result in too few holdings or an overconcentration in less carbon-intensive sectors, thereby raising idiosyncratic risk. Although Evans and Archer (1968), Statman (1987), and Campbell et al. (2001) concluded that portfolios of 20–50 stocks nearly eliminate unsystematic risk, later research by Statman (2004) and Domian et al. (2007) suggested that optimal diversification requires at least 160–300 stocks. Thus, given their narrower investment scope, low- and high-carbon funds may face elevated risk.

Evidence of portfolio-level idiosyncratic risk differences remains mixed. Bello (2005) found no diversification gap between ethically screened and conventional SRI funds. Humphrey and Tan (2014) reported that positively or negatively screened portfolios show similar risk–return profiles to unscreened ones. However, Pizzutilo (2017) found that MSCI SRI indices are less diversified and exhibit higher unsystematic risk. Ceccarelli et al. (2024) further show that low-carbon funds with the lowest carbon risk scores display greater volatility than medium-carbon funds, reflecting risk-sharing constraints.

We contribute to the literature on idiosyncratic risk and performance in two main ways. First, we quantify and compare idiosyncratic risks across low-, medium-, and high-carbon funds to derive diversification implications for both green and brown portfolios. Second, following portfolio selection theory (Markowitz, 1952) and the CAPM, which posit that idiosyncratic risk is typically uncompensated, we propose an augmented risk-adjusted performance measure that accounts for the opportunity costs of idiosyncratic risk (i.e., the compensation forgone by not investing in systematic risk). This idiosyncratic risk–adjusted measure enables a more comprehensive evaluation of mutual fund performance by considering both systematic and unsystematic components. It also clarifies whether investing in low- or high-carbon funds places investors at a disadvantage relative to more traditional strategies.

3. Data

We use survivorship bias–free mutual fund data from Morningstar Inc., which include monthly net and gross returns, fund characteristics, and quarterly portfolio information. We exclude index and specialty funds, those with average total net assets (TNA) below \$1 million, and funds with fewer than 24 months of return data (Elton et al., 2014).

Because our goal is to compare the performance of low-, medium-, and high-carbon funds, we rely on carbon data that Morningstar began reporting in 2017. We use quarterly portfolio-level CI, based on actual holdings, thereby avoiding potential greenwashing concerns common in self-proclaimed SRI classifications. With this information available at the portfolio level, our final dataset comprises 1827 actively managed U.S. domestic equity funds observed from January 2017 to December 2024, supplemented with return and risk factor data from January 2015 to support a 24-month rolling-window analysis without shortening the study period.

Sustainable fund definitions vary across studies. We classify funds as low-, medium-, or high-carbon according to their carbon emissions, given that climate change represents investors' leading concern (Macquarie, 2021) and the greatest global risk (World Economic Forum, 2022). Among available measures, portfolio CI serves as our key variable for assessing fund exposure, as it is less subject to methodological bias. Studies comparing ESG-based sustainability ratings show large discrepancies across providers (Berg et al., 2022; Chatterji et al., 2016) and evidence of retroactive adjustments (Berg et al., 2021). In contrast, a fund's CI is the asset-weighted average CI of its holdings, where each holding's CI equals the sum of Scope 1 and Scope 2 carbon dioxide equivalent (CO_2e) emissions (in tons) divided by company revenue (in millions of USD).

Scope 1 and Scope 2 emissions classify greenhouse gas (GHG) emissions from an organization's activities and serve as fundamental, methodology-independent indicators. Scope 1 emissions refer to direct CO_2e emissions within the organization, while Scope 2 emissions capture indirect CO_2e emissions from purchased fossil-based energy. Both are essential for assessing and managing environmental impact. For calculating a fund's portfolio CI, only long-position holdings with available company CI data are included. Their portfolio weights are then rescaled to sum to 100%. A lower CI denotes greater carbon efficiency, whereas a higher CI indicates lower efficiency, as companies emit more GHG to generate $1 million in revenue.

Table 1 reports descriptive statistics for our sample. The average fund size is slightly above $2.6 billion, with over 75% of fund-quarter observations showing smaller TNA, reflecting a right-skewed distribution. Roughly 20% of the sample comprises load funds, and the average expense ratio is 0.91% per year, ranging from 0% to 2.15%. The expense ratio is computed as the annualized difference between reported gross and net returns. Following Sirri and Tufano (1998), we derive each fund's implied percentage net flow using quarter-end TNA and quarterly returns. With an average net flow of −1.84% per quarter, the sample exhibits overall outflows during the study period. On average, funds hold 134 stocks, are 26 years old, and allocate about 40% of assets to institutional share classes.

Regarding fund activity, the mean turnover ratio of about 50% per year—calculated as the lesser of purchases or sales divided by average monthly TNA—indicates that half of a fund's portfolio is reallocated annually. Activity levels vary widely, from under 15% to over 100% at the 10th and 90th percentiles. In line with Cremers and Petajisto (2009), the average active share (AS) of 75%, computed as half the sum of absolute weight deviations from each fund's benchmark, shows that most managers in our dataset are actively manage their portfolios rather than replicate benchmarks. Even the minimum AS of roughly 25% exceeds the 20% threshold, confirming that the portfolios are not purely passive.

Regarding our carbon metric, we observe substantial variation in mutual fund sustainability. The mean CI is 150.35, with a standard deviation of 112.16. Percentile statistics further illustrate this dispersion, with CI values ranging from 13.31 at the minimum to 559.35 at the maximum.

To enable comparisons in subsequent analyses, we classify funds into low-, medium-, and high-carbon categories. This step is crucial because we assess sustainability based on each fund's actual portfolio CI rather than self-reported SRI indicators. Following the factor-construction framework of Fama and French (1993), low-carbon funds comprise the 30% with the lowest CI values, high-carbon funds the 30% with the highest, and the remaining 40% constitute medium-carbon funds, which largely represent conventional portfolios.

Because a fund's CI may change over time as portfolio holdings or company-level emissions evolve, relative rankings can shift. To maintain current and representative classifications, we sort funds into the 30–40-30 percentile groups on a quarterly basis.

Table 2 presents the fund-quarter allocations derived from this classification, including the number of funds, observations, and mean values. The total count of 3457 fund observations—934 low-, 1444 medium-, and 1079 high-carbon—exceeds the overall 1827 unique funds in the dataset due to the quarterly reallocation procedure.

The high-carbon group shows somewhat greater fund turnover, as indicated by its larger number of funds relative to the low-carbon group. This variation likely reflects the sensitivity of CI to fluctuations in company-level emission values.

Mean CI values increase across the low-, medium-, and high-carbon categories, consistent with our classification method. When sorting fund-quarter observations, the averages are 48.82 for low-carbon, 126.85 for medium-carbon, and 283.50 for high-carbon funds, with the latter nearly six times higher than the former.

4. Ex post performance of low-carbon funds

To address our first research question, "How low-, medium-, and high-carbon funds have performed in recent years," we decompose overall performance into factor-driven, characteristics-driven, and manager-driven components. Sections 4.1 and 4.2 evaluate excess returns using traditional and augmented factor models, while Section 4.3 employs multivariate panel regressions to assess the influence of fund characteristics and managerial skill.

4.1. Traditional factor models

We begin by estimating traditional performance measures widely used in literature. To ensure comparability with prior mutual fund studies, these measures also serve as a benchmark for the augmented models in Section 4.2. We first assess plain excess returns and risk-adjusted returns ("alpha") using the CAPM and the FF5/Carhart models.[1] To generate a time series of alphas, we follow Sharpe (1992) and apply rolling regressions (Eq. (1)). This method allows us to calculate out-of-sample performance (Eq. (2)) for each fund i in month $t+1$, using style betas estimated over the preceding 24-month period ending at t.

$$\begin{aligned} ER_{i,t} = & \alpha_{i,t} + \beta_{i,t}^{MKT} ER_{MKT,t} + \beta_{i,t}^{SMB} SMB_t + \beta_{i,t}^{HML} HML_t + \beta_{i,t}^{RMW} RMW_t \\ & + \beta_{i,t}^{CMA} CMA_t + \beta_{i,t}^{MOM} MOM_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

$$\begin{aligned} \alpha_{i,t+1}^{oos} = & ER_{i,t+1} - \Big(\beta_{i,t}^{MKT} ER_{MKT,t+1} + \beta_{i,t}^{SMB} SMB_{t+1} + \beta_{i,t}^{HML} HML_{t+1} \\ & + \beta_{i,t}^{RMW} RMW_{t+1} + \beta_{i,t}^{CMA} CMA_{t+1} + \beta_{i,t}^{MOM} MOM_{t+1} \Big) \end{aligned} \tag{2}$$

The monthly excess return of fund i in month t over the one-month treasury bill rate is denoted by $ER_{i,t}$, the excess return of the U.S. market by $ER_{MKT,t}$, and the error term by $\varepsilon_{i,t}$. Without additional factors, $\alpha_{i,t}$ represents the in-sample Jensen (1968) alpha of fund i during the observation window ending at tt. Adding the small-minus-big (SMB_t), High-Minus-Low (HML_t), Robust-Minus-Weak (RMW_t), Conservative-Minus-Aggressive (CMA_t), and Carhart (1997) Momentum (MOM_t) risk factors yields the six-factor model (FF5/Carhart). The corresponding style betas of fund i during the 24-month estimation window are $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SMB}$, $\beta_{i,t}^{HML}$, $\beta_{i,t}^{RMW}$, $\beta_{i,t}^{CMA}$, and $\beta_{i,t}^{MOM}$. The out-of-sample alpha for fund i in month $t+1$ is denoted $\alpha_{i,t+1}^{oos}$. Each fund's quarterly alpha equals the sum of its three monthly out-of-sample alphas.

Table 3 reports the univariate analysis of these models based on the CI-based classification into low-, medium-, and high-carbon funds. For comparison, it also presents results from the augmented performance models discussed in Section 4.2. We report mean values for net excess returns, alphas, style betas, and adjusted R^2. The market beta's significance is tested against one, while alphas and other betas are tested against zero using fund-level clustered standard errors. The "High − Low" column shows the return difference between high- and low-carbon funds along with its statistical significance from mean-comparison tests.

Our results show a statistically significant outperformance of low-carbon funds relative to high-carbon funds across traditional models, along with negative average alphas for all funds. Average quarterly excess returns range from 3.00% for low-carbon funds to 2.11% for high-carbon funds, implying a return differential of 0.88%. After adjusting for market risk using the CAPM, average quarterly alphas are −0.09% for low-carbon and − 0.85% for high-carbon funds. Although the spread narrows to 0.75%, it remains statistically significant at the 1% level. Including additional risk factors in the FF5/Carhart model further reduces the gap to 0.49%, but the difference remains significant. These findings align with Reboredo and Otero González (2022), confirming the superior performance of low-carbon funds over high-carbon counterparts.

Interestingly, low-carbon funds display higher market betas along with higher alphas across all model specifications. This pattern contrasts with the "beta anomaly" (Frazzini & Pedersen, 2014), and while an in-depth exploration of this relationship lies beyond the present scope, it represents a promising avenue for future research.

[1] We thank Kenneth French for providing the relevant factor returns at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1
Descriptive fund characteristic statistics.

	N	Mean	SD	Percentile						
				Min	10	25	50	75	90	Max
Turnover Ratio (% p.a.)	41,765	50.39	43.84	0.00	11.15	22.00	39.00	65.00	100.00	263.00
Active Share (%)	39,839	74.74	16.60	25.33	51.55	64.04	77.03	88.26	94.54	99.03
Net Flow (%)	41,695	−1.84	7.25	−26.37	−8.22	−4.40	−2.14	0.07	4.34	24.96
TNA ($M)	42,246	2630	6070	3	36	129	543	1962	6547	38,978
Expense Ratio (% p.a.)	42,098	0.91	0.34	0.00	0.51	0.72	0.90	1.09	1.28	2.15
Fund Age (years)	42,497	26.17	14.48	6.42	10.50	16.58	24.75	31.50	39.92	101.08
Holdings (#)	42,296	133.63	224.57	20.00	31.00	44.00	70.00	119.00	266.00	1930.00
Top10 Holdings (%)	40,545	32.42	13.02	5.70	16.95	22.74	30.74	41.42	50.50	65.83
Load Fund (Yes = 1 No = 0)	42,497	0.18	0.38	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Institutional (%)	42,497	41.64	37.99	0.00	0.00	0.07	34.30	79.66	99.85	100.00
Carbon Intensity	42,497	150.35	112.16	13.31	35.36	64.67	122.36	203.03	308.75	559.35

This table presents quarterly summary statistics for fund characteristics when sustainability information (CI) is available. The sample comprises 1827 actively managed U.S. domestic equity mutual funds from January 2017 to December 2024. "N" denotes the number of observations, "Mean" the equal-weighted average, and "SD" the standard deviation.
The turnover ratio is calculated as the lesser of purchases or sales divided by average monthly total net assets (TNA) per year. Active share is the sum of absolute portfolio weight deviations from the fund's benchmark index, divided by two, following Cremers and Petajisto (2009). Net flow is derived from quarterly TNA and returns, following Sirri and Tufano (1998). TNA represents the total net assets under management, reported in USD millions.
The expense ratio equals the quarterly average of the annualized difference between monthly gross and net returns. Fund age is based on the oldest share class. "Holdings" refers to the number of equity positions in the portfolio, while "Top10 holdings" represents the percentage of assets invested in the ten largest positions. "Load fund" is a binary indicator equal to one for funds with front-end or deferred load charges. "Institutional" indicates the percentage of the fund's TNA held in institutional share classes.
Carbon intensity (CI) is the asset-weighted average of the portfolio holdings' company-level CO_2 (and equivalent) emissions, measured in metric tons, divided by company revenue in USD millions.

Table 2
Fund classification based on carbon intensity.

	N	Funds	Category	N	Funds	Mean
Carbon Intensity	42,497	1827	Low	12,767	934	48.82
			Medium	16,995	1444	126.85
			High	12,735	1079	283.50

This table presents the number of funds and quarterly observations for low-, medium-, and high-carbon categories based on portfolio carbon intensity (CI). Low-carbon funds represent the bottom 30% with the lowest CI values, high-carbon funds the top 30% with the highest values, and the remaining 40% are classified as medium-carbon funds. Funds are re-sorted into these 30–40-30 percentile groups each quarter. The final column reports the corresponding mean values of the fund-quarter observations within each category.

4.2. Carbon augmented factor models

Fund managers of low-carbon funds should not be rewarded solely for allocating to low-carbon assets, as this decision primarily reflects the investor's chosen carbon exposure. Similar to traditional factor exposures, the relevant question is whether managers possess the skill to select superior stocks within the low-carbon universe, thereby generating excess value for investors. To investigate this, we augment the traditional factor models with two carbon factors constructed using a zero-investment portfolio approach. These extensions enable a more precise estimation of factor-driven performance arising from exposure to low- and high-carbon stocks and provide improved alpha estimates that capture managerial stock-picking ability.

To account for different investment strategies, we introduce two carbon-related BMG factors: one based on industry-independent CI to capture absolute exclusion strategies, and another based on industry-dependent CI to capture best-in-class approaches. The factor construction methodology follows standard asset pricing literature, as outlined by Fama and French (1993) and Görgen et al. (2020). For detailed descriptions, descriptive statistics, and intercorrelations with existing factors, see Appendix A.

The average returns of the industry-dependent BMG factor, reported in Table A1, show that low-carbon stocks outperformed high-carbon stocks during our sample period—consistent with the findings of Pástor et al. (2022) and Bauer et al. (2022). To reflect these differences, we incorporate the CI-based factors into the FF5/Carhart six-factor framework to derive a BMG-adjusted performance measure (Eq. (3)). Although only one of the two factors is statistically significant, both are included because they capture distinct investment strategies. Moreover, the factors are only weakly correlated (see Appendix A) and frequently take both positive and negative values over time, ensuring each contributes unique information to the decomposition of fund returns.

$$\begin{aligned}\alpha^{oos}_{i,t+1} =& ER_{i,t+1} - \Big(\beta^{MKT}_{i,t} ER_{MKT,t+1} + \beta^{SMB}_{i,t} SMB_{t+1} + \beta^{HML}_{i,t} HML_{t+1} \\ &+ \beta^{RMW}_{i,t} RMW_{t+1} + \beta^{CMA}_{i,t} CMA_{t+1} + \beta^{MOM}_{i,t} MOM_{t+1} \\ &+ \beta^{ind}_{i,t} BMG^{ind}_{t+1} + \beta^{dep}_{i,t} BMG^{dep}_{t+1}\Big)\end{aligned} \tag{3}$$

Here, $\alpha^{oos}_{i,t+1}$ denotes the out-of-sample alpha of fund i in month $t+1$, estimated analogously to Eqs. (1) and (2). Adding the industry-independent BMG (BMG^{ind}_{t+1}) and industry-dependent BMG (BMG^{dep}_{t+1}) factors produces seven- and eight-factor alphas, respectively. The corresponding BMG style betas—$\beta^{ind}_{i,t}$ and $\beta^{dep}_{i,t}$—are obtained from 24-month rolling regressions ending at t. This enhanced comparison among low-, medium-, and high-carbon funds enables assessment of whether low-carbon funds have maintained consistent outperformance beyond the effects of investing in low-carbon stocks.

The results in Table 3 show that incorporating the industry-independent CI factor into the FF/Carhart model (BMG I) reduces the difference in risk-adjusted performance between high- and low-carbon funds from −0.49% to −0.39%. Adding the industry-dependent BMG factor (BMG II) further narrows the gap to −0.11%. This reduction reflects the outperformance of low-carbon stocks within the same industry during the sample period, now captured by the carbon factors. Consequently, best-in-class strategies appear to play a key role when sorting funds by industry-dependent CI. Consistent with their sustainable investment objectives, low-carbon (high-carbon) funds exhibit significant negative (positive) factor loadings on the industry-dependent BMG factor of −0.067 (+0.076), indicating best-in-class (worst-in-class) behavior.

Strikingly, the performance gap between low- and high-carbon funds remains statistically significant at the 1% level across all models. However, the sharp decline in the return differential relative to the FF5/

Table 3
Univariate analysis based on traditional and augmented performance models.

`	Category	N	Alpha	High–Low	β MKT	β SMB	β HML	β RMW	β CMA	β MOM	β BMG IND	β BMG DEP	Adj. R^2
	Low	12,578	3.00***										
Excess Return	Medium	16,707	2.52***	−0.88***									
	High	12,457	2.11***										
	Low	12,584	−0.09***		1.004***								0.832
CAPM	Medium	16,731	−0.51***	−0.75***	0.969***								0.865
	High	12,505	−0.85***		0.928***								0.822
	Low	12,584	−0.07***		0.980***	0.052***	−0.105***	−0.085***	−0.174***	−0.005***			0.919
FF/Carhart	Medium	16,731	−0.33***	−0.49***	0.949***	0.109***	0.040***	0.005***	−0.017***	−0.027***			0.936
	High	12,505	−0.56***		0.913***	0.131***	0.153***	0.023***	0.092***	−0.063***			0.925
	Low	12,531	−0.13***		0.979***	0.047***	−0.113***	−0.082***	−0.160***	−0.009***	−0.007***		0.922
BMG I	Medium	16,648	−0.34***	−0.39***	0.947***	0.107***	0.038***	0.013***	−0.035***	−0.029***	0.055***		0.938
	High	12,467	−0.52***		0.906***	0.129***	0.159***	0.036***	0.034***	−0.065***	0.131***		0.928
	Low	12,531	−0.21***		0.977***	0.043***	−0.099***	−0.098***	−0.153***	−0.010***	0.004	−0.067***	0.923
BMG II	Medium	16,648	−0.25***	−0.11***	0.944***	0.102***	0.038***	0.012***	−0.032***	−0.031***	0.052***	0.025***	0.939
	High	12,467	−0.32***		0.904***	0.123***	0.150***	0.045***	0.034***	−0.069***	0.119***	0.076***	0.929

This table presents quarterly descriptive statistics on the net performance of low-, medium-, and high-carbon funds using traditional and augmented risk models. Funds with portfolio carbon intensity (CI) in the bottom 30% are classified as low-carbon, those in the middle 40% as medium, and those in the top 30% as high.
The column "Alpha" reports equal-weighted averages of quarterly excess and risk-adjusted returns. Excess returns are fund returns minus the one-month treasury bill rate. Risk-adjusted returns are out-of-sample alphas estimated using the capital asset pricing model (CAPM) and the Fama and French (2015) five-factor model combined with the Carhart (1997) momentum factor. The BMG I model incorporates an industry-independent Brown-Minus-Green (BMG IND) factor, while the BMG II model adds an industry-dependent factor (BMG DEP).
Out-of-sample alphas are obtained by subtracting the relevant risk factor returns from the fund's excess returns using style betas estimated from 24-month rolling regressions ending at $t - 1$. Each fund's quarterly alpha equals the sum of its three monthly out-of-sample alphas.
The column "High − Low" reports the difference in average returns between high- and low-carbon funds, accompanied by unpaired two-sample mean comparison tests. Columns "β MKT," "β SMB," "β HML," "β RMW," "β CMA," "β MOM," "β BMG IND," and "β BMG DEP" contain the average estimated style betas from the rolling regressions, while "Adj. R^2" reports the average adjusted R-squared.
Significance is tested against zero for Alpha, β SMB, β HML, β MOM, β BMG IND, and β BMG DEP, and against one for β MKT. Standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Carhart benchmark suggests that traditional risk factors alone cannot fully explain the performance gap between low- and high-carbon portfolios. With an average BMG II alpha of −0.21% per quarter, low-carbon funds still outperformed medium- and high-carbon funds, which recorded quarterly alphas of −0.25% and − 0.32%, respectively.

4.3. *Examining fund characteristics: Performance drivers beyond risk factors*

Thus far, we have observed that low-carbon funds outperform medium- and high-carbon funds. We next control for differences in fund characteristics—key determinants of performance such as annual turnover (reflecting portfolio reallocation and transaction costs; e.g., Carhart, 1997), AS for managerial activity (Cremers & Petajisto, 2009), TNA for scale effects (e.g., Indro et al., 1999), expense ratio and load indicators for fees and management costs (e.g., Dellva & Olson, 1998; Gil-Bazo & Ruiz-Verdú, 2009), and fund flows (e.g., Edelen, 1999). We first test whether these characteristics differ significantly across low-, medium-, and high-carbon funds, and then employ panel regressions to determine whether such differences explain alphas and the outperformance of low-carbon funds relative to the others.

Table 4 presents mean values and results of mean-comparison tests for low- and high-carbon fund characteristics. Fund activity differs significantly between the two groups in both AS and turnover. Managers of low-carbon funds, with an average AS of 72.20%, deviate about 6% less from their benchmarks than high-carbon managers, whose average AS is 78.84%. Similarly, low-carbon funds exhibit roughly 8.8% lower annual turnover.

Low-carbon funds in our sample are also slightly older (26.70 vs. 25.25 years) and have experienced smaller quarterly outflows (−1.65% vs. −2.03%). The average expense ratio ranges from 0.88% per year for medium-carbon funds to 0.90% for high-carbon and 0.95% for low-carbon funds.

Low- and high-carbon funds hold significantly fewer assets than medium-carbon funds (172 holdings), averaging only 80 holdings for low-carbon funds and 137 for high-carbon funds. Low-carbon funds also display higher portfolio concentration, with 40.78% of assets in their top ten holdings, compared with 26.78% for high-carbon funds and 30.63% for medium-carbon funds.

To decompose the alphas obtained from the factor models and assess whether low-carbon funds outperform due to superior managerial skill, we regress quarterly alphas on fund characteristics using the following panel specification:

$$\alpha^{oos}_{i,q+1} = \varphi_0 + \varphi_1 Low-Carbon_{i,q} + \varphi_2 High-Carbon_{i,q} + \sum_{m=3}^{M} \varphi_m Characteristics^m_{i,q} + \eta_{i,q+1} \tag{4}$$

Here, $\alpha^{oos}_{i,q+1}$ denotes the out-of-sample alpha of fund i in quarter $q+1$, estimated from the FF5/Carhart, BMG I, or BMG II models. $LowCarbon_{i,q}$ equals one for low-carbon funds and zero otherwise, while $HighCarbon_{i,q}$ identifies high-carbon funds. Medium-carbon funds serve as the reference group, represented by the intercept. $Characteristics^m_{i,q}$ captures the fund characteristics described earlier. Except for the carbon fund indicators, all explanatory variables are demeaned to allow unbiased comparison of intercepts across model specifications.

We estimate both pooled and year–fixed effects regressions and conduct coefficient comparison tests between low- and high-carbon funds. Standard errors are clustered at the fund level to account for heteroskedasticity and time-series correlation (e.g., Andrews, 1991).

Table 5 presents the regression results based on quarterly alphas calculated from net fund returns for the FF5/Carhart six-factor model (Columns M1–M3), the BMG I seven-factor model (M4–M6), and the BMG II eight-factor model (M7–M9).

The first column of each model (M1, M4, and M7) presents baseline regressions without fund characteristics or year fixed effects, corresponding to the performance comparisons in Sections 4.1 and 4.2. The results show a significant outperformance of low-carbon funds and a significant underperformance of high-carbon funds relative to medium-carbon funds.

After controlling for fund characteristics, the FF5/Carhart model (M2) indicates a smaller outperformance for low-carbon funds (32.31 bp vs. 20.70 bp per quarter) and a smaller underperformance for high-carbon funds (−16.45 bp vs. −10.45 bp). Both effects remain statistically significant at the 1% level, with similar results when year fixed effects are added (M3).

Incorporating fund characteristics into the BMG I regressions (M5 and M6) further reduces the performance gap, though significance persists. In the BMG II model (M7 and M8), high-carbon funds no longer differ significantly from medium-carbon funds, while low-carbon funds continue to outperform. This suggests that managers of low-carbon funds may have demonstrated superior stock-selection ability during the sample period. However, after introducing time fixed effects (M9), the outperformance of low-carbon funds relative to high-carbon funds

Table 4
Descriptive fund characteristic statistics sorted by carbon criteria.

	Category	N	Carbon Intensity
Turnover Ratio (% p.a.)	Low	12,570	45.69
	Medium	16,732	50.89
	High	12,463	54.47
	High − Low		8.78***
Active Share (%)	Low	11,947	72.20
	Medium	15,932	73.55
	High	11,960	78.84
	High − Low		6.65***
Net Flow (%)	Low	12,574	−1.65
	Medium	16,689	−1.85
	High	12,432	−2.03
	High − Low		−0.37*
TNA ($M)	Low	12,713	2662
	Medium	16,897	2891
	High	12,636	2250
	High − Low		−412
Expense Ratio (% p.a.)	Low	12,657	0.95
	Medium	16,860	0.88
	High	12,581	0.90
	High − Low		−0.05***
Fund Age (years)	Low	12,767	26.70
	Medium	16,995	26.47
	High	12,735	25.25
	High − Low		−1.46*
Number of Holdings	Low	12,709	80.11
	Medium	16,910	171.65
	High	12,677	136.58
	High − Low		56.46***
Top10 Assets (%)	Low	12,707	40.78
	Medium	16,910	30.63
	High	12,675	26.78
	High − Low		−14.00***
Load Fund	Low	12,767	0.18
	Medium	16,995	0.17
	High	12,735	0.19
	High − Low		0.01
Institutional (%)	Low	12,767	41.95
	Medium	16,995	41.24
	High	12,735	41.86
	High − Low		−0.09

This table presents quarterly descriptive statistics for fund characteristics by CI. Reported characteristics include annual turnover ratio, active share, quarterly net flow, total net assets (TNA, USD millions), annualized expense ratio, fund age (years), number of equity holdings, percentage invested in the top ten holdings, load fund indicator (yes = 1; no = 0), and the percentage of assets held by institutional investors.
For each characteristic, the column "CI" reports equal-weighted means for low-, medium-, and high-carbon fund groups, along with the "High − Low" ("No − Yes") differences shown in the final row. Standard errors are clustered at the fund level. *, **, and *** denote significance from an unpaired two-sample mean comparison test at the 10%, 5%, and 1% levels, respectively.

Table 5
Performance regression.

Alpha (Q + 1)	FF 5/Carhart			BMG I			BMG II		
	M1	M2	M3	M4	M5	M6	M7	M8	M9
Low-Carbon	0.3231***	0.2070***	0.1910***	0.2526***	0.1706***	0.1497***	0.0951***	0.1002**	0.0981**
	(0.0361)	(0.0408)	(0.0414)	(0.0375)	(0.0427)	(0.0431)	(0.0351)	(0.0417)	(0.0426)
High-Carbon	−0.1645***	−0.1045***	−0.0949***	−0.1260***	−0.0669**	−0.0576*	−0.0231	0.0130	0.0227
	(0.0311)	(0.0332)	(0.0335)	(0.0316)	(0.0339)	(0.0342)	(0.0313)	(0.0334)	(0.0334)
Turnover Ratio (% p.a.)		−0.0006	−0.0007*		−0.0000	−0.0002		−0.0010***	−0.0008**
		(0.0004)	(0.0004)		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Active Share (%)		−0.0097***	−0.0097***		−0.0099***	−0.0103***		−0.0018	−0.0015
		(0.0014)	(0.0014)		(0.0015)	(0.0015)		(0.0014)	(0.0014)
Net Flow (%)		0.0108***	0.0102***		0.0109***	0.0106***		0.0081***	0.0079***
		(0.0021)	(0.0021)		(0.0022)	(0.0022)		(0.0023)	(0.0023)
Ln TNA		−0.0067	0.0005		−0.0070	−0.0003		−0.0254***	−0.0179*
		(0.0092)	(0.0093)		(0.0095)	(0.0096)		(0.0091)	(0.0092)
Expense Ratio (% p.a.)		−0.2872***	−0.2544***		−0.2360***	−0.2122***		−0.3079***	−0.2800***
		(0.0594)	(0.0603)		(0.0627)	(0.0637)		(0.0592)	(0.0594)
Fund Age (years)		0.0015	0.0011		0.0017*	0.0015		0.0017*	0.0013
		(0.0009)	(0.0010)		(0.0010)	(0.0010)		(0.0010)	(0.0010)
Ln # Holdings		0.0129	0.0434		0.0042	0.0313		0.0565**	0.0598**
		(0.0290)	(0.0301)		(0.0303)	(0.0313)		(0.0285)	(0.0293)
Top10 Assets (%)		0.0079***	0.0108***		0.0062***	0.0086***		0.0041**	0.0062***
		(0.0021)	(0.0021)		(0.0022)	(0.0022)		(0.0020)	(0.0020)
Load Fund		0.0337	0.0278		0.0258	0.0217		0.0171	0.0084
		(0.0382)	(0.0385)		(0.0397)	(0.0399)		(0.0391)	(0.0392)
Institutional (%)		−0.0008**	−0.0005		−0.0008**	−0.0006		−0.0006	−0.0005
		(0.0004)	(0.0004)		(0.0004)	(0.0004)		(0.0004)	(0.0004)
Idiosyncratic Risk		0.1389***	0.1393***		0.0803***	0.0976***		−0.0124	−0.0545*
		(0.0255)	(0.0315)		(0.0253)	(0.0310)		(0.0240)	(0.0289)
Alpha (Q)		−0.0605***	−0.0646***		−0.0688***	−0.0686***		−0.0508***	−0.0508***
		(0.0064)	(0.0066)		(0.0065)	(0.0066)		(0.0062)	(0.0063)
Intercept	−0.3827***	−0.3814***	−0.3806***	−0.3841***	−0.3965***	−0.3930***	−0.2920***	−0.3162***	−0.3185***
	(0.0201)	(0.0217)	(0.0221)	(0.0207)	(0.0226)	(0.0229)	(0.0201)	(0.0220)	(0.0224)
Year Fixed Effects	No	No	Yes	No	No	Yes	No	No	Yes
Adjusted R^2	0.0049	0.0139	0.0419	0.0027	0.0115	0.0334	0.0003	0.0053	0.0221
N	37,172	37,172	37,172	37,172	37,172	37,172	37,172	37,172	37,172
P Value Coefficient Difference	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0016	0.0679	0.1173

This table reports the results of performance regressions using out-of-sample net alphas for quarter q + 1. The baseline model applies the Fama and French (2015) five-factor model combined with the Carhart (1997) momentum factor, with resulting alphas shown in columns (M1)–(M3). Columns (M4)–(M6) extend the model by adding the industry-independent Brown-Minus-Green (BMG) factor, and columns (M7)–(M9) include both industry-independent and industry-dependent BMG factors. Both the factor construction and fund classification—low-carbon (bottom 30%), medium-carbon (middle 40%), and high-carbon (top 30%)—are based on CI. Each fund's quarterly alpha equals the sum of its three monthly out-of-sample alphas. All models include indicator variables identifying whether a fund-quarter observation belongs to the low- or high-carbon group, with medium-carbon funds serving as the reference category (intercept).
Columns (M2), (M3), (M5), (M6), (M8), and (M9) include demeaned fund characteristics as controls, while columns (M3), (M6), and (M9) also add year fixed effects. Standard errors are clustered at the fund level, with robust values reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The *p*-value of the coefficient difference tests the significance between the low- and high-carbon indicator coefficients.

loses statistical significance in the coefficient comparison test.

Examining the controls in the BMG II model reveals that turnover and expense ratios negatively affect risk-adjusted performance, whereas net flows, number of holdings, and the share invested in the top ten holdings have positive effects. Lagged out-of-sample alphas are also included as a control, with a significantly negative coefficient, indicating no performance persistence. Overall, the relatively lower trading activity, higher top-ten concentration, and smaller outflows of low-carbon funds contributed positively to their outperformance, while their smaller number of holdings and higher expense ratios detracted from it.

Following economic intuition, it is noteworthy that across models with controls, the coefficients for expense ratio (measured annually) affect alphas (measured quarterly) by −0.21 to −0.31. This implies a near one-to-one relationship: a 100 bp increase in annual expenses reduces annual performance by roughly 96–124 bp. The regression intercepts further indicate an average fund underperformance relative to the market of about 0.30–0.40% per quarter, or 1.2–1.6% annually.

Although the adjusted R^2 values of our regressions appear low, this is expected because the dependent variable—out-of-sample alpha—represents residual, risk-adjusted returns after accounting for factor exposures. Most variation is therefore idiosyncratic and difficult to explain through observable fund characteristics.

5. Opportunity costs of idiosyncratic risk

While the underperformance of high-carbon funds becomes insignificant once we control for the outperformance of low-carbon stocks and differences in fund characteristics, low-carbon funds continue to show superior risk-adjusted performance compared with medium-carbon funds. This raises the question of whether their outperformance stems from superior stock selection or from bearing higher idiosyncratic risk. To address this, we extend our analysis beyond conventional performance components to tackle our second research question, "What are the opportunity costs of idiosyncratic risk, and how do they affect the financial performance of investors in low-, medium-, and high-carbon funds?" The following subsections first quantify funds' idiosyncratic risks and then adjust the previously estimated alphas for the corresponding opportunity costs.

5.1. Idiosyncratic risk in low-carbon funds

As the descriptive statistics in Section 4.3 indicate, low-carbon funds tend to hold relatively few securities, raising concerns about limited diversification (Domian et al., 2007; Statman, 2004). In addition, the focus on low- and high-carbon stocks further constrains diversification, as certain sectors are systematically underweighted or excluded while others are overweighted, leading to sector overconcentration (Ceccarelli et al., 2024).

Table 6 reports the means, medians, and standard deviations of the quarterly root mean-squared errors (RMSEs) from the 24-month rolling performance regressions described in Eq. (1). Results are based on net returns and are presented for the FF5/Carhart, BMG I, and BMG II factor models. As expected, medium-carbon funds exhibit the lowest average idiosyncratic risk across all models. High-carbon funds show slightly higher risk, whereas low-carbon funds display the highest idiosyncratic risk by a considerable margin. The magnitude of these differences is emphasized by statistically significant gaps between low-, medium-, and high-carbon funds at the 1% level, ranging from 0.15% to −0.40%. Overall, idiosyncratic risk declines as additional factors are introduced, consistent with the models' improved explanatory power.

To examine whether funds with very low or very high CI indeed face higher idiosyncratic risk, we conduct a more granular analysis by sorting all funds into deciles based on portfolio CI. Fig. 1 plots the average BMG II RMSE for each decile and quarter. The resulting U-shaped pattern indicates that funds in the extreme deciles—those with very low or very high CI—exhibit elevated idiosyncratic risk. Consistent with Table 7, low-carbon funds display higher idiosyncratic risk than their high-carbon counterparts. The minimum risk level occurs around Deciles 6 and 7, closer to high-carbon than to low-carbon funds. This finding reinforces the 30–40-30 sorting results, which also revealed significantly greater risk among low-carbon funds.[2]

5.2. Idiosyncratic risk adjusted performance

Section 5.1 shows that investments in both low- and high-carbon funds involve elevated idiosyncratic risk. The next question is how this risk affects investors' financial performance. According to portfolio selection theory (Markowitz, 1952) and the CAPM, idiosyncratic risk is not compensated, whereas systematic market risk is. To account for this, we calculate the opportunity costs associated with idiosyncratic risk and subtract them from the previously estimated alphas. These opportunity costs represent the returns investors could have earned by bearing systematic rather than idiosyncratic risk.

$$OpportunityCost_{i,t+1} = \frac{\mu_{MKT}}{\sigma^2_{MKT,[t-23;t]}} MSE_{i,[t-23;t]} \tag{5}$$

Here, $OpportunityCost_{i,t+1}$ denotes the opportunity cost of fund i in month $t+1$, representing a leveraged market premium. To estimate this premium, the expected market return (μ_{MKT}) is divided by the time-varying market variance, calculated from the preceding 24 months of market returns. This ratio is then multiplied by the fund's mean squared error ($MSE_{i,[t-23;t]}$) from the rolling regressions described in Eq. (1), which captures the fund's idiosyncratic risk. A time-varying market variance accounts for fluctuations in market risk. μ_{MKT} is set to 0.72% per month, reflecting the long-term average U.S. market return from January 1990 to December 2024. Each fund's quarterly opportunity cost is computed as the sum of its three monthly values.

Table 7 presents means and pairwise comparison tests for all three fund categories under the FF5/Carhart, BMG I, and BMG II models, alongside the averages and differences for opportunity costs and idiosyncratic risk–adjusted alphas.

The column "Alpha Unadjusted" summarizes the baseline univariate and multivariate results (Table 5 M1, M4, and M7), which show significant performance differences across low-, medium-, and high-carbon funds. On average, low-carbon funds have the highest alphas and high-carbon funds the lowest. The next column, "Opportunity Cost of Idiosyncratic Risk," reports the corresponding costs, while "Alpha Idiosyncratic Risk Adjusted" presents the resulting alphas after deducting these costs.

The findings indicate that the opportunity costs of idiosyncratic risk are both economically and statistically significant. Based on mean-squared error values from the BMG II model, average quarterly opportunity costs range from 0.16% for medium- and high-carbon funds to 0.22% for low-carbon funds, exerting a notable effect across all categories. As shown in Section 5.1, the largest performance reduction occurs for low-carbon funds, reflecting their elevated idiosyncratic risk. With an average difference of 6 bp per quarter (≈24 bp annually), investors in low-carbon funds bear greater diversification costs than those in medium-carbon funds. In contrast, the gap between medium- and high-carbon funds is marginal (≈1 bp). However, as Fig. 1 illustrates, funds at the extremes of CI—very low or very high—face even higher idiosyncratic risks, implying an even stronger drag on performance.

The average idiosyncratic risk–adjusted alpha consistently declines once the opportunity costs of idiosyncratic risk are incorporated. Because low-carbon funds bear higher opportunity costs, the performance gap between high- and low-carbon funds narrows—from −43 bp under the FF5/Carhart model to an insignificant −6 bp under BMG II. Consequently, low-carbon funds no longer outperform high-carbon funds, as their higher idiosyncratic risk offsets the earlier characteristics-driven advantage. This is also reflected in the insignificant 2 bp difference between low- and medium-carbon funds, while high-carbon funds continue to underperform medium-carbon funds.

6. Expected performance of low-carbon funds

The preceding sections provided ex post assessments of fund performance. We now address the third research question, "What financial performance can investors expect from low-carbon funds in the future?" Ex post analyses alone only partially inform this forward-looking perspective.

First, investors should consider ex ante expected factor premia and factor loadings rather than relying solely on realized returns. These premia primarily compensate for traditional risk factors such as market, size, and value. Standard models (e.g., CAPM, Fama and French (2015) five-factor model, and Carhart (1997) momentum factor) offer a framework for assessing expected premia. Our results indicate that investors in low-carbon funds may anticipate slight underperformance relative to medium- and especially high-carbon funds, largely due to systematically negative exposures to the value and investment factors.

Beyond traditional factors, emerging theory highlights distinct carbon-related factor premia. Pástor et al. (2021) propose a negative "greenium" for low-carbon stocks—reflecting their nonmonetary utility to environmentally motivated investors—and a positive "carbon risk premium" for high-carbon stocks, owing to their greater sensitivity to shifts in the economic transition. Consequently, ceteris paribus, investors should expect lower returns from low-carbon funds than from medium- and high-carbon funds.

Second, investors should anticipate general underperformance relative to benchmarks, as indicated by negative alphas across all fund categories. Performance differences are also expected to depend on fund characteristics. Assuming persistence of the ex post relationships observed in Section 4.3, higher activity, higher expenses, and limited diversification will continue to weigh on ex ante performance. Nonetheless, if fund characteristics remain stable, investors in low-carbon funds may still achieve marginally higher returns on average than those in medium- or high-carbon funds.

Third, concentrated investments in low-carbon stocks reduce the investable universe and limit diversification due to fewer holdings and sector overconcentration. Under-diversified investors, in particular, should account for the opportunity costs of forgone factor premia that could be earned through passive, market-wide benchmarks. Assuming

[2] To test for systematic differences in idiosyncratic risk, we regress the quarterly RMSE on nine decile indicator variables, controlling for fund characteristics. The U-shaped relationship remains significant and robust, particularly at the extremes of the distribution. Detailed regression results are available upon request.

Table 6
Univariate analysis of idiosyncratic risk.

RMSE	Category (Mean)	Differences (Diff)	N	Mean	Diff	Median	SD
	(1) Low	(1)–(2)	12,547	2.28	0.40***	2.04	1.13
FF/Carhart	(2) Medium	(2)–(3)	16,676	1.88	−0.17***	1.76	0.95
	(3) High	(1)–(3)	12,479	2.05	0.23***	1.95	0.86
	(1) Low	(1)–(2)	12,547	2.23	0.37***	2.03	0.99
BMG I	(2) Medium	(2)–(3)	16,676	1.86	−0.15***	1.74	0.90
	(3) High	(1)–(3)	12,479	2.01	0.22***	1.92	0.81
	(1) Low	(1)–(2)	12,547	2.21	0.37***	2.00	0.98
BMG II	(2) Medium	(2)–(3)	16,676	1.84	−0.15***	1.72	0.90
	(3) High	(1)–(3)	12,479	2.00	0.22***	1.90	0.82

This table presents the means, medians, and standard deviations of the quarterly root mean squared error (RMSE) derived from 24-month rolling performance regressions based on net returns. Results are shown for the Fama and French (2015) five-factor model combined with the Carhart (1997) momentum factor, as well as for the BMG I and BMG II models. The BMG I model incorporates a carbon-intensity-based, industry-independent Brown-Minus-Green (BMG IND) factor, while the BMG II model adds an industry-dependent factor (BMG DEP).
The quarterly RMSE equals the average of three monthly values multiplied by $\sqrt{3}$. Statistics are reported for funds classified as low-carbon (bottom 30%), medium-carbon (middle 40%), and high-carbon (top 30%) according to portfolio CI. The "High − Low" column reports the difference in average RMSE between high- and low-carbon funds, accompanied by an unpaired two-sample mean comparison test. Standard errors are clustered at the fund level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

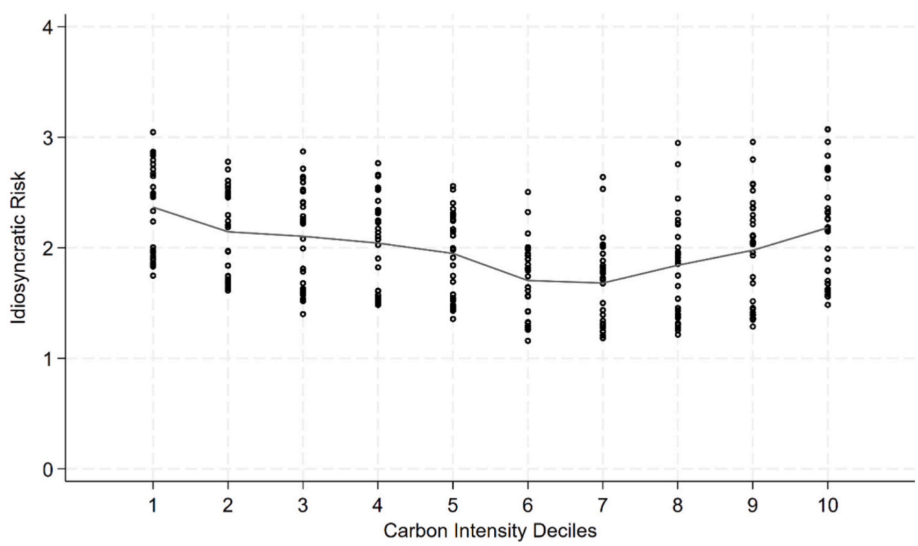

Fig. 1. Idiosyncratic risk for carbon intensity deciles.
This figure plots the average root mean squared error (RMSE) for each decile and quarter, representing carbon intensity-sorted funds over the period from 2017/01 to 2024/12. The line shows the overall mean of each decile. A fund's quarterly RMSE is obtained from 24-month rolling window performance regressions based on net returns, using the BMG II model. The BMG II model augments the Fama and French (2015) five factor model combined with the Carhart (1997) momentum factor with a carbon intensity-based industry-independent Brown-Minus-Green (BMG) factor and an industry-dependent BMG factor. The quarterly RMSE is the quarter-average of the three monthly calculated RMSE values, multiplied by the square root of three. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

persistent idiosyncratic risk, these opportunity costs remain substantial. Investors in low-carbon funds are therefore more adversely affected, leading to expected underperformance relative to medium-carbon funds. Accordingly, those lacking broader diversification across multiple funds or portfolios should recognize that the higher idiosyncratic risk of low-carbon funds can significantly diminish financial performance.

7. Conclusion

The debate over the financial performance of conventional versus sustainable investment funds has persisted for years. Despite extensive research, prior studies often relied on coarse measures or lacked a detailed decomposition of the components driving performance, leaving ex ante expectations unclear. To inform investors, asset managers, and other market participants, this study analyzes low-, medium-, and high-carbon funds by addressing three central questions.

First, how have low-, medium-, and high-carbon funds performed in recent years, and what drove these outcomes? On average, all fund categories underperformed their benchmarks. However, traditional factor models show that low-carbon funds outperformed high-carbon funds. Because these models fail to capture systematic return differences between low- and high-carbon stocks, we introduced augmented models incorporating industry-independent and industry-dependent carbon factors. The results reveal a smaller yet significant outperformance of low-carbon funds. After controlling for fund characteristics, these differences narrow further, indicating that low-carbon fund managers may possess distinct stock-picking skills.

Second, what are the opportunity costs of idiosyncratic risk for low-carbon funds? Both low- and high-carbon funds exhibit elevated idiosyncratic risk. To quantify its impact, we propose an idiosyncratic risk–adjusted alpha that deducts a notional market return representing systematic risk exposure. The findings show substantial opportunity

Table 7
Performance comparison of funds based on idiosyncratic risk.

	Category (Mean)	Differences (Diff)	N	Alpha Unadjusted		Opportunity Costs of Idiosyncratic Risk		Alpha Idiosyncratic Risk Adjusted	
				Mean	Diff	Mean	Diff	Mean	Diff
	(1) Low	(1)–(2)	12,547	−0.07***	0.26***	0.24***	0.08***	−0.31***	0.19***
FF/Carhart	(2) Medium	(2)–(3)	16,676	−0.34***	0.23***	0.16***	−0.01**	−0.50***	0.24***
	(3) High	(1)–(3)	12,479	−0.56***	0.49***	0.18***	0.06***	−0.74***	0.43***
	(1) Low	(1)–(2)	12,531	−0.13***	0.21***	0.22***	0.07***	−0.36***	0.14***
BMG I	(2) Medium	(2)–(3)	16,648	−0.34***	0.18***	0.16***	−0.01**	−0.50***	0.19***
	(3) High	(1)–(3)	12,467	−0.52***	0.39***	0.17***	0.05***	−0.69***	0.34***
	(1) Low	(1)–(2)	12,531	−0.21***	0.04	0.22***	0.06***	−0.44***	−0.02
BMG II	(2) Medium	(2)–(3)	16,648	−0.25***	0.07**	0.16***	−0.01**	−0.41***	0.08***
	(3) High	(1)–(3)	12,467	−0.32***	0.11***	0.17***	0.05***	−0.49***	0.06

This table presents quarterly means and differences for adjusted and unadjusted out-of-sample net alphas of low-, medium-, and high-carbon funds based on the Fama and French (2015) five-factor model combined with the Carhart (1997) momentum factor, as well as the BMG I and BMG II models. The BMG I model incorporates a carbon-intensity–based, industry-independent Brown-Minus-Green (BMG IND) factor, while the BMG II model adds an industry-dependent factor (BMG DEP). Funds with CI values in the bottom 30% are classified as low-carbon, those in the middle 40% as medium, and those in the top 30% as high-carbon.
The column "Alpha Unadjusted" reports equal-weighted averages of out-of-sample alphas obtained by subtracting risk factor returns from fund excess returns using previously estimated style betas from t − 1. "Opportunity Costs of Idiosyncratic Risk" shows the average notional market returns a fund could have earned by assuming systematic rather than idiosyncratic risk, representing the corresponding opportunity cost. "Alpha Idiosyncratic Risk Adjusted" reports the mean difference between the unadjusted alpha and the calculated opportunity cost.
Each column also presents differences ("Diff") between low-, medium-, and high-carbon funds, accompanied by unpaired two-sample mean comparison tests. The significance of means is tested against zero. Standard errors are clustered at the fund level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

costs across all fund categories, highest for low-carbon funds.

Third, what financial performance can investors expect from low-carbon funds in the future? Considering the persistence of performance components, we advise investors to evaluate ex ante expected factor premia and factor loadings rather than rely solely on historical returns. A potentially negative greenium for low-carbon stocks and a positive "carbon risk premium" for high-carbon stocks are particularly relevant. Thus, despite past outperformance, investors should anticipate lower future returns for low-carbon funds relative to medium- and high-carbon funds once these theoretical factors are considered.

Overall, mutual funds generally underperform passive, market-wide benchmarks with similar styles, as reflected in consistently negative alphas. Differences in manager skill and fund characteristics will continue to shape performance, implying marginally better expectations for low-carbon funds. Nevertheless, investors should remain mindful of the opportunity costs linked to limited diversification and sector concentration—effects that are especially pronounced in low-carbon portfolios.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the author(s) used ChatGPT (GPT-5, OpenAI) in order to perform a language check. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

Declaration of competing interest

None.

Appendix A. Factor construction and descriptive statistics

The construction of the industry-independent and -dependent BMG carbon factors follows Fama and French (1993) and Görgen et al. (2020). We obtain U.S. stock-level data from Refinitiv, including Scopes 1 and 2 emissions, revenues, market capitalizations, and monthly returns, yielding a dataset of 5349 stocks. To classify low-, medium-, and high-carbon stocks, we calculate each company's CI by dividing total Scopes 1 and 2 emissions by revenue.

The procedure mirrors that of Fama and French (1993) in creating the HML factor. At the end of each June, we independently sort stocks into portfolios based on size and sustainability characteristics. First, we classify stocks as green (low-carbon), neutral (medium-carbon), or brown (high-carbon) using the 30th and 70th percentile breakpoints from sustainability data as of the prior December. Second, we categorize stocks as small or big according to the median market capitalization at the end of June. This yields six intersection portfolios (i.e., Small Green (SG), Small Neutral, Small Brown (SB), Big Green (BG), Big Neutral, and Big Brown (BB)) for which we compute monthly value-weighted returns.

For the industry-independent BMG factor, stocks are sorted into brown and green portfolios regardless of industry. The bottom 30% of stocks with the lowest CI are labeled green and the top 30% with the highest CI as brown. Large stocks have market capitalizations above the median; small stocks fall below. Following Eq. (A1), the BMG factor return equals the difference between the average returns of the brown portfolios (SB and BB) and the green portfolios (SG and BG):

$$BMG_t^{ind} = \frac{1}{2}\left(SB_t^{ind} + BB_t^{ind}\right) - \frac{1}{2}\left(SG_t^{ind} + BG_t^{ind}\right) \tag{A1}$$

The factor return for month t of the industry-independent BMG factor is denoted BMG_t^{ind}. The value-weighted monthly returns of the portfolios are represented as SB_t^{ind}, BB_t^{ind}, SG_t^{ind}, BG_t^{ind} for the Small Brown, Big Brown, Small Green, and Big Green portfolios, respectively.

For the second factor, we introduce an industry-dependent BMG factor. Here, stocks are first classified as green or brown within each industry, rather than across the entire market. This design captures additional return differences arising from potential best-in-class strategies, which are commonly employed in sustainable investment portfolios. Industry classification follows the Thomson Reuters Business Classification (TRBC), and we adjust CI values within each sector using a z-scoring normalization approach[3]:

$$z_{i,j,t} = \frac{\left(CI_{i,j,t} - \overline{CI}_{j,t}\right)}{SD\left(CI_{j,t}\right)} \tag{A2}$$

Here, $z_{i,j,t}$ denotes the z-score of company i in industry j for month t. It is calculated as the difference between the company's observed CI ($CI_{i,j,t}$) and the industry mean ($\overline{CI_{j,t}}$) for that month, divided by the corresponding industry standard deviation of CI. At the end of each June, stocks with the highest (lowest) CI within each industry are sorted into the SB (SG) and BB (BG) portfolios based on these z-scores. Following Eq. (A3), the industry-dependent factor is computed as

$$BMG_t^{dep} = \frac{1}{2}\left(SB_t^{dep} + BB_t^{dep}\right) - \frac{1}{2}\left(SG_t^{dep} + BG_t^{dep}\right) \tag{A3}$$

where BMG_t^{dep} represents the industry-dependent BMG factor return for month t, while SB_t^{dep}, BB_t^{dep}, SG_t^{dep}, and BG_t^{dep} are the value-weighted monthly portfolio returns.

We evaluate both factors by analyzing their returns, intercorrelations, and relationships with established factors. Panel A of Table A1 reports percentiles, standard deviations, and average monthly returns of the CI-based factors from January 2017 to December 2024. Both exhibit negative average values, though only the industry-dependent factor is statistically significant—indicating potential outperformance for long-short portfolios based on CI. Specifically, a zero-investment portfolio long in high-carbon and short in low-carbon stocks yields an economically meaningful average monthly return of −0.43% (−5.16% annually). This result aligns with Pástor et al. (2022), who report a 0.65% monthly outperformance for green stocks from November 2012 to December 2020.

Panel B of Table A1 reports factor correlations to assess potential multicollinearity. The industry-independent BMG factor based on CI shows a statistically significant correlation with the industry-dependent CI factor (−25.29%). Although somewhat unexpected—since the factors are intended to capture distinct investment strategies and thus should yield non-redundant stock sorting—the correlation remains moderate relative to other factor relationships.

Correlations between the industry-independent CI factor and the established Fama–French and Carhart momentum factors range from −4.75% to 56.97%. For comparison, among traditional factors, the strongest intercorrelation occurs between the value (HML) and investment (CMA) factors at 65.04%.

The industry-dependent BMG factor also displays statistically significant correlations with several Fama–French and Carhart factors. However, their magnitudes are not concerning, as confirmed by the variance inflation factors in the regression analyses in Sections 4.1 and 4.2, all of which remain well within acceptable limits.

Table A.1
Descriptive statistics of BMG factors.

Panel A–Factor Returns

	N	Mean	SD	Percentile						
				Min	10	25	50	75	90	Max
BMG CI IND	96	−0.24	1.67	−4.25	−2.11	−1.60	−0.38	1.04	1.82	4.03
BMG CI DEP	96	−0.43***	1.27	−4.30	−1.91	−1.21	−0.50	0.59	1.03	2.53

Panel B – Factor Correlation

	BMG CI IND	BMG CI DEP	ER_{MKT}	SMB	HML	RMW	CMA
BMG CI DEP	25.29%**						
ER_{MKT}	2.10%	−21.99%**					
SMB	8.90%	22.65%**	32.19%***				
HML	37.99%***	44.65%***	3.83%	35.08%***			
RMW	6.72%	−24.61%***	4.65%	−37.79%***	15.17%		
CMA	56.97%***	30.46%***	−22.89%**	0.80%	65.04%***	14.19%	
MOM	−4.71%	−8.79%	−41.6%***	−45.55%***	−25.83%**	−6.27%	8.89%

This table presents descriptive statistics in Panel A for the Brown-Minus-Green (BMG) factor–mimicking portfolios over the period January 2017 to December 2024. Following Fama and French (1993), stocks are independently sorted into six portfolios at the end of each June using the median market capitalization and the 30th and 70th percentile breakpoints of their sustainability information. The monthly factor return is calculated as the difference between the average returns of the Small Brown and Big Brown portfolios and those of the Small Green and Big Green portfolios.
Two versions of the factor are constructed: an industry-independent carbon intensity factor (BMG CI IND) and an industry-dependent carbon intensity factor (BMG CI DEP). For the latter, carbon intensity (CI) values are standardized using z-scores within industries classified by Thomson Reuters Business Classification (TRBC) codes.
Panel A reports the percentiles, standard deviations, and mean factor returns, where the mean represents the monthly average return of a zero-investment portfolio long in brown and short in green stocks.
Panel B reports correlations between the newly developed factors and the established Fama and French (2015) five-factor and Carhart (1997) momentum factors. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

[3] According to the TRBC classification, the economic sectors include Energy, Basic Materials, Industrials, Consumer Cyclicals, Consumer Non-Cyclicals, Financials, Healthcare, Technology, Utilities, Real Estate, Institutions, Associations & Organizations, Government Activity, and Academic & Educational Services. Companies lacking TRBC codes are grouped under the category "Unknown." We also perform adjustments at a more granular level using TRBC business sector codes, which encompass 34 industries, and find that the results remain economically unchanged.

Appendix B. Variable descriptions

Table B.1
Variable descriptions.

TNA	Total net assets managed by fund (millions USD)
Ln TNA	Ln [Total net assets managed by fund]
Expense Ratio	Quarterly average annualized difference between fund's monthly gross and net returns
Load Fund	Indicator for funds with front or deferred load charges
Turnover Ratio	Fund's annual turnover = (Lesser of purchases or sales)/AVE monthly total net assets
Active Share	$\sum$ Absolute portfolio weight differences from benchmark/2 (Cremers & Petajisto, 2009)
Net Flow	% Net flow calculated quarterly TNA and returns (Sirri & Tufano, 1998)
Fund Age	Age of fund (years), derived from the oldest share class
Institutional	% Fund TNA attributable to institutional share classes
Holdings	#Equity holdings in portfolio
Ln Holdings	Ln {#Equity holdings in portfolio]
Top10 Holdings	% Assets invested in fund's 10 largest holdings
Carbon Intensity (CI)	Asset-weighted AVE portfolio holdings' underlying company CO^2 (and equivalents) emissions in metric tons/Company revenue (million USD)
Low-Carbon	Indicator for funds in bottom 30% with lowest CI based on quarterly resorting
High-Carbon	Indicator for funds in top 30% with highest CI based on quarterly resorting
Excess Return (ER)	Fund net return −1-month treasury bill rate
Alpha (Unadjusted) (α^{oos})	Risk-adjusted net fund return based on out-of-sample calculation using CAPM, Fama and French (2015) 5-factor model/ Carhart (1997) momentum factor, and BMG I and II models. BMG models include carbon intensity-based industry-independent and -dependent factors
ER_{MKT}	Excess return of U.S. market over 1-month treasury bill rate
SMB	Fama and French (2015) small–big risk factor return, capturing size effect
HML	Fama and French (2015) high–low risk factor return, capturing value effect
RMW	Fama and French (2015) robust–weak risk factor return, capturing profitability
CMA	Fama and French (2015) conservative–aggressive risk factor return, capturing investment
MOM	Carhart (1997) momentum risk factor return
BMG IND	Carbon intensity (CI) industry-independent brown–green factor return using Fama and French (1993)
BMG DEP	Return of the carbon intensity-based industry-dependent Brown-Minus-Green factor using the Fama and French (1993) methodology
β MKT	Market factor beta obtained by regressing fund excess returns on risk factor models
β SMB	Small–big factor beta obtained by regressing fund excess returns on risk factor
β HML	High–low factor beta obtained by regressing fund excess returns on risk factor
β RMW	Robust–weak factor beta obtained by regressing fund excess returns on risk factor
β CMA	Conservative–aggressive factor beta obtained by regressing fund excess returns on risk factor
β MOM	Momentum factor beta obtained by regressing fund excess returns on risk factor models
β BMG IND	Industry-independent brown–green carbon factor beta obtained by regressing fund excess returns on risk factor
β BMG DEP	Industry-dependent brown–green carbon factor beta obtained by regressing fund excess returns on risk factor
Adj. R^2	Adjusted R obtained by regressing fund excess returns on risk factor
Alpha Characteristics Adjusted	Risk-adjusted fund net returns − Characteristic-driven performance component
Opportunity Costs of Idiosyncratic Risk (*OpportuntiyCost*)	Notional expected return when taking systematic instead of idiosyncratic market risk
Alpha Idiosyncratic Risk Adjusted	Risk-adjusted fund net return − Opportunity costs of idiosyncratic risk
Alpha Idiosyncratic Risk and Characteristics Adjusted	Risk-adjusted fund net return − Characteristic-driven performance component + Opportunity cost of idiosyncratic risk
RMSE	Root mean squared error from regressing fund excess returns on risk factor
MSE	Mean squared error from regressing fund excess returns on risk factor
μ_{MKT}	Expected market return derived from long-term AVE market return from January 1990 to January 2022
σ^2_{MKT}	Market variance derived from market returns over past 24 months
z	Industry-adjusted z-scores of firm CI or risk based on Thomson Reuters Business Classification codes
SB IND	Small brown value-weighted portfolio return based on stocks with market capitalization below median + CI in top 30% using industry-independent sorting
BB IND	Big brown value-weighted portfolio return based on stocks with market capitalization above median + CI in top 30% using industry-independent sorting
SG IND	Small green value-weighted portfolio return based on stocks with market capitalization below median + CI in bottom 30% using industry-independent sorting
BG IND	Big green value-weighted portfolio return based on stocks with market capitalization above median + CI in bottom 30% using industry-independent sorting
SB DEP	Small brown value-weighted portfolio return based on stocks with market capitalization below median + CI in top 30% using industry-dependent sorting
BB DEP	Big brown value-weighted portfolio return based on stocks with market capitalization above median + CI in top 30% using industry-dependent sorting
SG DEP	Small green value-weighted portfolio return based on stocks with market capitalization below median + CI in bottom 30% using industry-dependent sorting
BG DEP	Big green value-weighted portfolio return based on stocks with market capitalization above median + CI in bottom 30% using industry-dependent sorting
BMG CI IND	Carbon intensity-based industry-independent brown–green return factor using Fama and French (1993)
BMG CI DEP	Carbon intensity-based industry-dependent brown–green return factor using Fama and French (1993)

This table provides descriptions of variables used in this study, including appendices.

Data availability

The authors do not have permission to share data.

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