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Low carbon transition risk in mutual fund portfolios: Managerial involvement and performance effects

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Abstract

Transitioning to a low-carbon economy to mitigate the effects of climate change involves risks. We investigate the effects of managerial ownership and management on the low carbon transition risk of mutual fund portfolios and the effects of low carbon transition risk on mutual fund performance and flows. Using low carbon transition risk ratings based on the unmanaged carbon risk of the companies included in fund portfolios, we find that managerial ownership and the socially responsible focus of the fund reduce fund portfolio exposure to carbon risk, whereas active management has the opposite effect. Furthermore, we find that funds with low carbon transition risk produce a better risk-adjusted performance are more sensitive to tail risks and exhibit a better fund flow performance.

KEYWORDS

carbon transition risk, manager ownership, mutual fund flows, mutual fund performance, mutual funds, socially responsible investment

1 | INTRODUCTION

Mitigating the adverse effects of climate change requires the transition to a low-carbon economy which, in turn, conveys specific risks that are acquiring priority in managerial decision-making by institutional investors (Krueger et al., 2020; Morningstar, 2018).[1] Managers are facing pressure from stakeholders to tackle fund portfolio exposure to the long-term environmental and regulatory risks implied by the transition to a decarbonized economy.[2]

In this article, we examine how the involvement of managers—as owners and decision-makers—affects the carbon risk embedded in mutual fund portfolios and how, in turn, this low carbon transition risk exposure impacts mutual fund performance and flows. Examining the drivers behind, and impact of, mutual fund exposure to low carbon transition risks is of interest to two main groups: (a) investors interested in resilient investments, who, in the face of long-term shifts to a decarbonized economy, require information that adequately reflects

[1]Several initiatives have recently been launched in order to achieve a greater commitment to low-carbon investment by institutional investors. The Portfolio Decarbonization Coalition (PDC) was co-founded in 2014 by the United Nations Environment Programme (UNEP), the UNEP Finance Initiative (UNEP FI), AP4, Amundi and CDP. Likewise, the Montreal Carbon Pledge, launched in 2014, aims to encourage institutional investors to commit to the measurement and disclosure of their carbon footprint, promote portfolio decarbonization and report carbon information in portfolio design as a means to facilitate investments at the service of the transition to a low-carbon economy.

[2]Those risks include, among others, tail risks from natural disasters related to climate change (e.g. floods, droughts and storms, rising sea levels and increasing temperatures) as well as the risk of stranded assets. Around 1300 mutual fund families are exposed to asset stranding risk, representing around 24% of the net asset value of mutual funds domiciled in the United States (Shakdwipee, 2017). Pension funds are also very exposed on the asset side because their holdings are invested in long-duration portfolios with important weightings in carbon-intensive industries (Messervy, 2016).

climate risks and opportunities affecting asset allocation, and (b) policymakers concerned with the reallocation of private and public funds to low-carbon economic activities.[3]

We first examine the relationship between managerial issues and fund portfolio low carbon risk, specifically whether managerial co-investment affects the low carbon risk level of the fund portfolio. Jensen and Meckling (1976), Smith and Stulz (1985) and Ma and Tang (2019) show that managerial ownership is a mechanism that alleviates agency conflicts, leading to a lower level of portfolio risk when managers are risk-averse. In investing their wealth, therefore, we can expect such managers to lower all kinds of fund risks—including carbon risk, that is, if managers are risk-averse, we can expect a negative relationship between managerial ownership and portfolio carbon risk. We also explore what role management team size plays in shaping the portfolio carbon risk, as Patel and Sarkissian (2017) show that team-managed funds are less exposed to risk than single-managed funds. In addition, we analyse the relationship between the carbon risk exposure and the social concerns of fund managers, as reflected in socially responsible investment (SRI). Although previous studies (e.g. Borgers et al., 2015; Duran et al., 2019; El Ghoul & Karoui, 2017; Ibikunle & Steffen, 2017; Riedl & Smeets, 2017) show mixed effects for SRI impact on mutual fund performance, we expect that tilting investments using social considerations will have a positive effect in reducing portfolio carbon risk exposure. Finally, since active management has been shown to have an impact on fund performance that depends on specific market conditions (e.g. Cremers et al., 2016; Pástor et al., 2015), we expect that selective and active fund management will have potential effects on exposure to carbon risk. According to Tan et al. (2019), the construction of portfolios with a low carbon risk should achieve good performance in the long term once the effect of the risk is recognized by the market. We therefore elucidate whether active fund management, which allows managers to select strategies according to carbon risk exposure, leads to lower or higher carbon risk for the fund portfolio.

In contrast to previous studies that use carbon emissions as a proxy for low carbon risk, we use carbon risk ratings, which are computed on the basis of the unmanaged carbon risk remaining in a company after all actions by the company to mitigate carbon risk exposure are taken into consideration. Those unmanaged carbon risks are rated by Sustainalytics with a carbon risk score (CRS) calculated, from low to high, as negligible (0), low (0–10), medium (10–30), high (30–50) and severe (greater than 50).[4] Thus, the CRS provides information of the vulnerability of the firm's value to transition to a low-carbon economy. On the basis of this information, Morningstar Direct Mutual Fund[5] provides investors with information on the carbon risk embedded in mutual fund portfolios as a weighted sum of the Sustainalytics carbon risk ratings, with weights determined by the portfolio share of the company. The Morningstar portfolio CRS ratings, publicly made available to investors on a quarterly basis, can be used to set a baseline for assessment of the fund's capacity to manage carbon risk. Contrary to the portfolio carbon footprint metric, which only assesses fund exposure to carbon emissions, the Morningstar CRS metric provides accurate information on actual carbon risk exposure; thus, a portfolio with a low CRS is better positioned to transition to a decarbonized economy than a portfolio with a high CRS.

For a sample of 1223 US domestic equity mutual funds with portfolios CRS-rated by Morningstar Direct Mutual Fund each quarter over the period January 2017 (when the CRS metric started to be computed) to December 2018, we document that the portfolio CRS decreases as managerial ownership increases; that is, fund portfolios with greater managerial ownership stakes are embedded with lower portfolio carbon risk. Furthermore, our empirical tests confirm that team size is not related to fund portfolio carbon risk; that is, the number of fund managers does not affect investment decisions regarding carbon risk. Not surprisingly, we find that social screening—as reflected in the SRI focus of the fund—has a negative effect on the fund portfolio CRS, indicating that SRI practices are consistent with reduced exposure to low carbon transition risks. Finally, our evidence indicates that active fund management, measured by the inverse of R-squared (Amihud & Goyenko, 2013), increases the CRS of the fund in the subsequent year/quarter. This is consistent with the idea that active fund management pursues short-term profits and, consequently, outweighs carbon-intensive businesses in portfolios, thereby increasing the portfolio's exposure to carbon transition risks.

We also examine whether the CRS shapes fund performance and flows by analysing how the CRS affects risk-adjusted fund returns performance. Previous research (Borgers et al., 2015; Ibikunle & Steffen, 2017) suggests that funds with greater exposure to socially sensitive stocks show a poorer risk-adjusted performance. In considering carbon risk management, our empirical results indicate that managers effectively tackle carbon risk in their managerial decisions in such a way that the CRS is negatively related to next-quarter risk-adjusted fund performance. This result, which holds after controlling for different fund characteristics and model specifications, shows that funds dealing with low carbon transition risks are unlikely to experience impaired profitability. We also analyse the relationship between the CRS and fund returns volatility, finding that funds with lower CRS ratings are associated with significantly lower returns volatility in the next year/quarter. We also find that funds with lower CRS ratings consistently display lower levels of market risk exposure and co-skewness. This evidence is in line with the idea that funds concerned with risk management are also tackling low carbon transition risks in their management decisions. In regard to downside risk, however, we find that fund portfolios with low CRS ratings are more sensitive to market

[3]The United Nations Climate Change Conference of Paris 2015 specifically drew attention to the importance and need to channel financial resources towards economic activities that transform the productive structure of economies into low-greenhouse-gas-emission economies. The International Energy Agency estimates that, in the energy sector alone, investment amounting to USD37 trillion will be needed by 2035, so investments flows need to be redirected from high-carbon technologies at greater risk to low-carbon technologies (Schmidt, 2014).

[4]https://www.sustainalytics.com/

[5]https://www.morningstar.com/

tail risk than funds with portfolios with higher CRS ratings. Thus, fund portfolios with reduced exposure to low carbon transition risks offer better risk-adjusted returns, but they do so at the cost of less protection against tail risks. Finally, in line with Reboredo and Otero (2021), we examine the relationship between the CRS and flows, finding that the CRS of fund portfolios is negatively related to fund flows, which indicates that investors are taking carbon risk levels into account in their investment decisions.

Our study contributes to several strands of the extant literature on mutual funds. First, we provide insights on managerial ownership and risk-taking in the funds sector. Khorana et al. (2007), Evans (2008), Fu and Wedge (2011) and Ma and Tang (2019) show that managerial ownership reduces risk-taking and improves portfolio performance. Similarly, Karagiannis and Tolikas (2019) show that fund managers who risk their own capital are less likely to assume tail risk. By considering carbon risk management, our article complements previous studies that report that managerial ownership aligns managers' risk-taking incentives, as funds with greater managerial ownership are associated with mitigated low carbon transition risk.

Second, we contribute to the literature that contends that team management shapes portfolio risk and performance (Bar et al., 2011; Bliss et al., 2008; Patel & Sarkissian, 2017; Prather & Middleton, 2002). Consistent with most studies reporting that team-managed funds perform no better than single-managed funds, our evidence shows that team size is not decisive in determining the carbon risk level of a fund portfolio.

Third, our study is broadly related to the SRI mutual fund literature, given that carbon risk management involves the screening of companies according to SRI undertakings in relation to carbon risk management. Unlike previous studies on the effects of SRI on fund performance that report mixed results (see, among others, Bollen, 2007; Joliet & Titova, 2018; Nofsinger & Varma, 2014; Renneboog et al., 2008, 2011), in examining whether the SRI nature of a fund leads managers to reduce carbon risk exposure, we find that funds committed to SRI also have portfolios with reduced low carbon transition risks.

Fourth, we contribute to the literature on active portfolio management (Amihud & Goyenko, 2013; Cremers & Petajisto, 2009; Kacperczyk et al., 2008; Pástor et al., 2015) by reporting evidence that actively managed funds shape low carbon transition risks, in that funds with lower R-squared values perform poorly in terms of portfolio carbon risk management. Overall, our evidence shows that managerial features are relevant to shaping fund portfolio CRS.

Finally, our study fits within the flourishing literature on the effects of low carbon screening on portfolio performance. Several studies have explored how hedging climate risk affects portfolio performance, showing that reducing carbon exposure does not seem to impair portfolio performance (see, e.g. Andersson et al., 2016; De Jong & Nguyen, 2016; Ji et al., 2021; Trinks et al., 2018). Ibikunle and Steffen (2017), in contrast, show that green mutual funds significantly underperform relative to conventional funds, while Reboredo et al. (2017) and Marti-Ballester (2019) show that investors pay a premium for going green via renewable energies. Differing from those studies, we explore whether accounting for carbon risk management is likely to have detrimental effects on the portfolio performance of mutual funds, concluding that a reduced low carbon transition risk has favourable effects on risk-adjusted performance. This evidence is consistent with that of Dimson et al. (2015), who find that engaging in environmental or social issues enhances the accounting performance of US public companies.

The remainder of the paper is laid out as follows. Section 2 describes data, variable definitions and descriptive statistics. Section 3 explores the impact of managerial variables on the CRS of mutual fund portfolios and describes a robustness analysis. Section 4 discusses the effect of portfolio CRS on mutual fund performance and flows and the corresponding robustness analysis. Finally, Section 5 summarizes our results and concludes the paper.

2 | DATA, VARIABLE DEFINITIONS AND DESCRIPTIVE STATISTICS

This section describes a sample of equity mutual funds that have portfolios with CRS ratings and also the variables used to study determinants and the effects of fund portfolio exposure to carbon risk.

2.1 | Data

Since 2017, the Morningstar Direct Mutual Fund database has provided an assessment of the carbon transition risk embedded in a fund portfolio in the form of a CRS. This metric is computed on a quarterly basis as an asset weighting of the Sustainalytics carbon risk rating for companies included in the fund portfolio. Sustainalytics computes this rating on the basis of (a) the company's exposure to carbon risk, determined by the kind of business, operations and products and services of the company; and (b) the company's carbon risk management, which reflects its ability to manage carbon risks such as carbon emissions, energy efficiency and greener products and services. Accordingly, Sustainalytics assigns carbon risk ratings depending on unmanageable carbon risks that remain after taking into account management actions designed to diminish carbon risk exposure. As mentioned above, the CRS is based on five carbon risk categories, ranging from negligible risk (0) to maximum risk (greater than 50). On the basis of carbon risk information from Sustainalytics, Morningstar provides investors with information on the exposure of a mutual fund portfolio to low carbon transition risk by reporting the CRS, computed as a weighted sum of a company's Sustainalytics CRS rating, with weights determined by the portfolio share of the company.[6]

We assemble data for all US open-end equity mutual funds with portfolios that are rated with a CRS each quarter by the Morningstar Portfolio CRS. Our sample covers the period from January 2017 (when the CRS metric started to be computed) to December 2018.

[6]Further details about the procedure to compute the CRS for mutual funds can be found at https://www.morningstar.com/lp/measuring-transition-risk.

Our survivor-bias-free database includes mutual funds within the A share class,[7] which—to avoid Evans' (2008) incubation bias—are older than 2 years. Funds in the database are categorized into one of the following nine Morningstar equity fund categories: large blend (LB), large growth (LG), large value (LV), mid-cap blend (MB), mid-cap growth (MG), mid-cap value (MV), small blend (SB), small growth (SG) and small value (SV). We therefore exclude equity funds such as bond funds, money market funds, funds of funds, index funds and real estate funds. As a result of this filtering process, the final sample resulted in 1223 mutual funds.

For the funds, we also retrieve specific information as follows: fund names and tickers, inception date, daily price information and quarterly portfolio CRS score, total net assets and total assets, annual information on expense ratio and turnover, manager names, managerial ownership and the SRI focus, if any, of the fund (a dummy variable equal to 1 if the fund declares that it applies an SRI policy and 0 otherwise).

2.2 | Mutual fund variable definitions

2.2.1 | Managerial ownership and decisions

Fund managers shape a fund's portfolio CRS either through their involvement in ownership of the fund's portfolio (Khorana et al., 2007; Ma & Tang, 2019) or through managerial decisions taken on the basis of their utility functions.

From Morningstar Direct Mutual Fund, we retrieve annual information on (a) the number of managers in charge of the fund; and (b) manager ownership stakes in the fund for 2017 and 2018. Managerial ownership is required to be disclosed by the US Securities and Exchange Commission (SEC), since 2005, using the following USD investment ranges: 0, 1–10,000; 10,001-50,000; 50,001–100,000; 100,001–500,000; 500,001-1,000,000; and above 1,000,000. As the information within each interval is not precise in terms of invested USD, to estimate ownership, we use an interval regression approach whereby managerial ownership within each investment range is explained as a function of several covariates that include equity fund category, fund size, annual return, age, turnover and the SRI dummy. From that model,[8] we obtain the annual amount invested by each manager within the corresponding interval. We then aggregate the annual amount invested by the managers in charge of each fund. The ratio between this amount and the total asset value of the fund is taken as a quarterly measure of managerial ownership.[9]

Furthermore, since an SRI focus shapes managerial decisions according to non-economic principles such as environmental responsibility, human rights, religious views and good employee relations, we consider this indicator variable to be a potential determinant of the carbon risk exposure of a fund.

Finally, we assess the potential impact of active management on the fund's exposure to carbon risk by considering the quarterly R-squared value from the multifactor model in Equation 1, inversely related to active management of the fund and selectivity (see Amihud & Goyenko, 2013).

2.2.2 | Risk-adjusted performance

We estimate the quarterly adjusted performance of each fund as the alpha of the five-factor time series regression model, as proposed by Fama and French (2015, 2017) and augmented by Carhart's (1997) momentum factor:

$$\begin{aligned} R_{i,t} - R_{F,t} = {} & \alpha_i + \beta_{i,M} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,RMW} RMW_t \\ & + \beta_{i,CMA} CMA_t + \beta_{i,MOM} MOM_t + \varepsilon_{it}, \end{aligned} \tag{1}$$

where R_{it} is the daily fund i's return at day t; R_{Ft} is the risk-free return on the 1-month US treasury bill rate; MKT_t is the excess return of the market portfolio; SMB_t is the difference between diversified portfolio returns for small and large assets; HML_t is the difference between high book-to-market and low book-to-market portfolio returns; RMW_t is the difference between the returns for a diversified portfolio of robust and weak profitability assets; CMA_t is the difference between portfolio returns for low (conservative) and high (aggressive) investment firms; and, finally, MOM_t captures the momentum factor. The beta parameters in Equation 1 capture the sensitivity of excess returns to the six factors, whereas the alpha parameter α_i denotes the risk-adjusted performance of fund i.

For each year-quarter, we estimate the regression model in Equation 1 for each fund i and obtain the quarterly fund's α_i using daily information for that quarter regarding the fund's price excess return and information for the set of pricing factors, as sourced from the Kenneth French data library.[10]

2.2.3 | Mutual fund risk

Mutual fund risk is characterized in terms of volatility and downside risk. For quarterly periods, mutual fund volatility is measured using realized volatility (volatility) computed for each fund i as $\sqrt{\sum_{t=1}^{T} R_{it}^2}$, where R_{it} is fund i's continuous daily return for day t of the corresponding quarter.

Moreover, we account for the quarterly exposure of fund i to changes in aggregate stock market volatility using the implied market volatility beta obtained from the following regression (see Ang et al., 2006):

[7]Some mutual funds offer multiple share classes, which usually differ in fee structure and clientele (e.g. retail funds and institutional funds). We therefore aggregate all share classes given that considering different classes for the same fund as separate funds is misleading as they offer the same gross return before expenses.

[8]Results for the interval regression are reported in Appendix A.

[9]Alternatively, managerial ownership can be defined as the total USD amount invested by the management over total net assets. Empirical evidence reported below is not affected by this alternative definition of managerial ownership.

[10]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$$R_{i,t}-R_{F,t}=\alpha_i+\beta_{i,M}MKT_t+\beta_{i,VIX}\Delta VIX_t+\varepsilon_{i,t}, \tag{2}$$

where ΔVIX_t is the change in the implied S&P 100 option volatility index at day t and $\beta_{i,VIX}$ is the implied market volatility beta of fund i, estimated on a quarterly basis using daily data for that quarter. Data for the VIX index come from the Chicago Board Options Exchange.

Finally, we assess whether a fund tends to undergo positive or negative deviations with the market by computing the quarterly co-skewness risk measure (see Harvey & Siddique, 2000), which, for fund i, is given by

$$\text{Co-Skew}_{i,t}=\frac{E\left(\varepsilon_{i,t},MKT_t^2\right)}{\sqrt{E\left(\varepsilon_{i,t}^2\right)E\left(MKT_t^2\right)}}, \tag{3}$$

where $\varepsilon_{i,t}=(R_{i,t}-R_{F,t})-\alpha_i+\beta_{i,M}MKT_t$ is the residual of the factor time series regression in Equation 1 considering a single factor, namely, the excess returns of the market portfolio.

Regarding tail risk, we consider mutual fund exposure to aggregate tail risk in both the mutual fund sector and the overall market.

First, the sensitivity of the fund's returns to tail risk in the mutual fund industry is given by the downside beta ($\beta_{i,tail}$) in the following regression model:

$$R_{i,t}-R_{F,t}=\alpha_i+\beta_{i,M}MKT_t+\beta_{i,tail}ES_t+\varepsilon_{i,t}, \tag{4}$$

where $\beta_{i,tail}$ accounts for the sensitivity of fund i returns to downside risk in the mutual fund sector, given by the expected shortfall (ES) of the Vanguard Total Stock Market Index Fund (VTSMX) as representative of the mutual fund market. For the VTSMX returns index (r_t), ES—defined as $E\left[r_t \middle| r_t \le F_t^{-1}(q)\right]$, where $F_t^{-1}(q)$ is the inverse of the returns distribution function of the returns index at time t (the value at risk) for a confidence level q—is computed for a student-t return distribution as

$$ES_t(q)=\mu_t-\frac{\sigma_t}{q}\,h\left(H^{-1}(q)\right)\left(\frac{\upsilon+H^{-1}(q)^2}{\upsilon-1}\right), \tag{5}$$

where h and H denote the standard student-t density and cumulative distribution functions with υ degrees of freedom, respectively, and μ_t and σ_t^2 denote the mean and variance of the student-t density, assumed to be given by autoregressive and threshold general autoregressive conditional heteroskedasticity (GARCH) models, respectively. On a quarterly basis for each fund i, we estimate tail risk loading, $\beta_{i,tail}$, using daily information for the corresponding quarter on excess returns, excess market returns and ES values for a 5% confidence level.

Second, to assess the exposure of mutual fund i to overall downside risk in the stock market, we consider the exposure of each fund to the CBOE VIX Tail Hedge (VXTH) index. The VXTH index addresses downside risk in the stock market by tracking the performance of portfolios that buy and hold the S&P 500 index and buy 1-month 30-delta call options on the VIX index, with portfolio weights that change on a monthly basis depending on the likelihood of a black-swan event occurring according to the forward value of VIX. Falls in the index reflect increases in downside risk probability as perceived by the market. Using information on downside risk embedded in the VXTH index, the exposure of fund i returns is determined using the following regression model:

$$R_{i,t}-R_{F,t}=\alpha_i+\beta_{i,M}MKT_t+\beta_{i,VXTH}VXTH_t+\varepsilon_{i,t}, \tag{6}$$

where $\beta_{i,VXTH}$ is the downside beta that accounts for the sensitivity of fund i returns to downside risk in the stock market. For each fund i, the market tail risk loading $\beta_{i,VXTH}$ is estimated on a quarterly basis using daily data for the VXTH sourced from the Chicago Board Options Exchange.

2.2.4 | Other variables

We consider additional mutual fund features as given by the following variables: flows, fund size, fund age, expense ratio, turnover ratio and SRI. We measure quarterly fund flows as

$$\text{Flows}_{i,t}=\frac{TNA_{i,t}-TNA_{i,t-1}(1+r_{i,t})}{TNA_{i,t-1}}, \tag{7}$$

where $TNA_{i,t}$ reflects the total net assets of fund i at the end of quarter t and $r_{i,t}$ is the return on fund i at quarter t. Fund size is measured as the log of the market value of the fund's total assets at the end of the quarter. Fund age is measured as the years in existence of the fund at the end of the quarter calculated from the fund's inception date. The quarterly expense ratio is obtained as one-fourth of the annual gross expense ratio, defined as the percentage of total net assets charged each year to cover all expenses incurred by the fund (including management fees and administrative fees). Finally, taken as the annual turnover ratio is the fund's trading activity, accounting for trading activity as the percentage ratio of minimum of aggregate purchases and sales over average monthly net assets. To avoid distortion effects from outliers, flow and turnover variables are winsorized at the 99% and 1% levels.

2.3 | Descriptive statistics

Our sample consists of 1223 equity funds covering 9784 quarterly observations. Panel A in Table 1 shows that the average quarterly CRS is 11.27, with maximum and minimum values of 58.38 and 0, respectively. The distribution of the CRS across funds—depicted in Figure 1—shows asymmetries, with a large (small) amount of funds in the lowest (highest) quantiles and with most funds (74%) attaining CRS ratings between 7 and 16 and only a small proportion (3.4%) attaining CRS ratings above 20.

Around 68% of the sampled funds have co-investing managers, holding an average share of 0.37% of the total assets, as shown

TABLE 1 Summary statistics

Variables	Mean	Std. dev.	Max	Min	Skewness	Kurtosis	Percentiles 5%	25%	50%	75%	95%	Corr. CRS
Panel A. Carbon risk measure												
CRS	11.27	5.93	58.38	0.00	2.97	18.55	4.04	8.28	10.86	13.24	17.92	1
Panel B. Managerial ownership and decision variables												
Ownership (%)	0.37	2.05	54.66	0.00	15.55	321.97	0.00	0.00	0.02	0.13	1.31	−0.03
Team size	2.71	1.92	21.00	1.00	3.20	19.28	1.00	2.00	2.00	3.00	6.00	−0.03
SRI	0.09	0.29	1.00	0.00	2.87	9.22	0.00	0.00	0.00	0.00	1.00	−0.08
R-squared	0.69	0.27	0.99	0.01	−0.63	2.11	0.18	0.47	0.78	0.92	0.98	−0.10
Panel C. Risk-adjusted performance												
Alpha	−0.03	0.10	0.29	−1.54	−3.01	25.63	−0.21	−0.06	−0.01	0.01	0.09	0.04
β_M	0.86	0.28	3.15	−1.36	−0.77	7.49	0.37	0.71	0.92	1.02	1.22	−0.09
β_{SMB}	−0.01	0.26	2.50	−2.96	−0.34	14.50	−0.34	−0.14	−0.04	0.13	0.39	0.07
β_{HML}	−0.05	0.35	2.80	−4.57	−0.80	16.24	−0.55	−0.21	−0.03	0.13	0.41	0.15
β_{RMW}	−0.09	0.42	4.07	−8.79	−2.23	36.23	−0.72	−0.20	−0.04	0.09	0.36	−0.31
β_{CMA}	0.13	0.56	8.79	−3.97	3.09	31.98	−0.52	−0.10	0.07	0.27	0.99	0.41
β_{MOM}	−0.03	0.25	3.64	−2.31	−0.21	18.19	−0.42	−0.13	−0.02	0.10	0.31	−0.22
Panel D. Risk measures												
Volatility	6.94	4.82	89.01	2.13	4.04	37.31	3.27	4.07	5.28	8.45	15.63	−0.01
β_{VIX}	−0.04	0.16	2.90	−1.76	0.79	27.71	−0.27	−0.09	−0.02	0.02	0.18	0.01
Coskew	−0.02	0.19	0.64	−2.12	−2.55	25.14	−0.32	−0.10	0.00	0.08	0.21	0.07
β_{tail}	0.06	0.64	22.20	−2.88	16.16	400.16	−0.27	−0.06	0.01	0.08	0.38	−0.04
β_{VXTH}	0.08	0.56	3.59	−6.10	−0.78	12.37	−0.70	−0.14	0.04	0.30	1.00	−0.17
Panel E. Other variables												
Flows	−0.002	0.19	1.20	−0.93	3.97	22.51	−0.19	−0.05	−0.02	0.01	0.22	−0.03
Size	19.91	1.99	26.02	13.13	−0.04	3.07	16.58	18.55	20.01	21.22	23.09	−0.10
Age	16.73	12.04	96.61	2.13	2.53	13.74	3.33	8.69	15.30	21.66	33.41	−0.05
Expense	0.31	0.09	1.24	0.06	2.92	25.72	0.19	0.26	0.30	0.34	0.42	0.10
Turnover	63.91	65.42	507.00	2.00	3.97	25.02	8.89	27.00	49.00	80.00	154.69	0.06

Notes: The table reports summary statistics for the variables used in our analysis, listed in the first column: carbon risk score (CRS), managerial ownership, team size (number of managers), socially responsible investment (SRI), R-squared, risk-adjusted returns (Alpha), betas for the six-factor model, volatility (realized volatility), betas with respect to the market volatility, co-skewness, betas with respect to mutual fund and market downside risks; flows, fund size (log of total assets), age, expense ratio and turnover. The sample includes 1223 equity mutual funds for quarters 2017-I to 2018-IV, totalling 9784 observations. Summary statistics includes mean, standard deviation, maximum, minimum, skewness, kurtosis and percentiles (5%, 25%, 50%, 75% and 95%) for all the variables. The last column reports the linear Pearson correlation between CRS and the variables indicated in the first column.

in Panel B in Table 1. While the average number of managers in the management team is 2.71, there is wide dispersion across funds regarding team size. Only around 9% of the funds have an SRI focus. Funds also differ in terms of selectivity and active management: R-squared has a mean value of 0.69, reflecting that a significant fraction of the fund's returns are explained by the factor model in Equation 1, for a maximum of 0.99 and a minimum of 0.01.

Panel C in Table 1 shows that the average risk-adjusted return performance is negative (−0.03), with a large standard deviation and a negatively skewed distribution. Average values for the market beta parameter from the factor regression model in Equation 1 indicate that excess equity mutual fund returns mostly co-move with excess market returns, with an average beta of 0.86 and a low standard deviation. For the remaining pricing factors, average values indicate that equity fund excess returns move in the opposite direction to the SMB, HML, RMW and MOM factors and in the same direction as the CMA factor; sensitivities to those factors shows great dispersion across funds.

As for fund risk measures, shown in Panel D in Table 1, the descriptive statistics indicate that volatility has an average quarterly value of 6.94 and vary widely across funds. Likewise, the sensitivity of fund returns to stock market volatility is heterogeneous across funds, exhibiting both positive and negative sensitivities to stock market

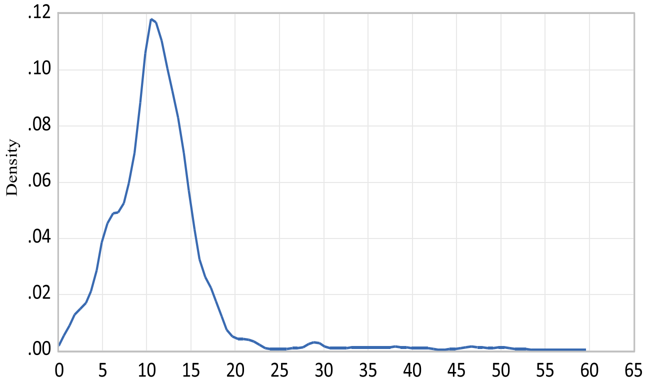

FIGURE 1 Distribution of CRS for US equity mutual funds for quarters 2017–2018 [Colour figure can be viewed at wileyonlinelibrary.com]

volatility swings. Similarly, descriptive evidence on co-skewness indicates the existence of funds that experience both positive and negative deviations with the market. Furthermore, downside betas indicate that fund returns have similar average values to downward movements in the funds sector and in the overall stock market, with average values of 0.06 and 0.08, respectively; however, the percentile information indicates that fund returns may increase or decrease with downside risks.

Panel E in Table 1 shows that the distribution of fund flows is decidedly skewed to the right, with a mean value near zero and with moderate flow dispersion among funds. Fund size on average is 19.9, and distribution is approximately symmetric. The mean fund age is 16.7 years, with most funds aged over 7 years. The quarterly average expense ratio is 0.31, with low dispersion among funds. Finally, the annual average value for turnover is 63.9.

The final column of Table 1 reports the linear Pearson correlation coefficients for the CRS and the variables indicated in the first column. Managerial co-investment and team size are negatively associated with CRS ratings, consistent with the fact that more 'skin in the game' is associated with lower carbon risk exposure. Similarly, SRI aims and R-squared values are negatively related with fund CRS. There is a positive linear association between the CRS and risk-adjusted returns that is consistent with the fact that returns are greater when there is more exposure to carbon risk. Likewise, the CRS correlates negatively with the market beta, indicating that funds with less carbon risk are more sensitive to movements in market excess returns. CRS ratings move positively with the SMB, HML and CMA pricing factors and negatively with the RMW and MOM pricing factors. Returns volatility and sensitivity of returns to stock market volatility are weakly related to the CRS, whereas co-skewness is positively related to the CRS. However, the CRS is negatively associated with downside betas, indicating that a low CRS goes hand in hand with greater sensitivity to downside risk. Finally, the CRS is negatively associated with fund flows (an increase in the CRS reduces fund flows) and is negatively correlated with fund size and fund age, and the higher the CRS, the higher the expense and turnover ratios.

3 | DO MANAGERIAL FEATURES AFFECT THE CARBON RISK OF MUTUAL FUNDS?

In this section, we first outline the empirical methods and results for the impact of managerial features—such as ownership, management team size, SRI and active management—on the carbon risk of mutual fund portfolios and then check the robustness of our baseline results.

3.1 | Managerial involvement and carbon risk

To examine the impact of managerial involvement on the CRS of mutual fund portfolios, we estimate the following regression model:

$$CRS_{i,t} = \omega + \beta O_{i,t-1} + \gamma T_{i,t-1} + \lambda SRI_{i,t-1} + \varphi R^2_{i,t-1} + \theta Controls_{i,t-1} + \varepsilon_{i,t}, \tag{8}$$

where the dependent variable, $CRS_{i,t}$, is the logit transformation of the portfolio CRS of mutual fund i at the year-quarter t: $CRS_{i,t} = log\left(\frac{CRS_{i,t}}{100-CRS_{i,t}}\right)$.[11] The main independent variables of interest are the managers' share in fund ownership ('skin in the game') as given by the variable $O_{i,t}$, the number of managers at the helm of the fund as indicated by the variable $T_{i,t}$, the SRI focus of the fund, $SRI_{i,t}$, and, finally, active fund management as given by the variable $R^2_{i,t}$. The parameters β, γ, λ and φ capture the marginal effects of those variables on the value of the logit transformation of the CRS. As for control variables, we include variables related to the main fund features and risk variables that may influence the CRS. Specifically, as carbon risk management may differ according to investment styles, we control for fixed effects style dummies defined according to the nine Morningstar equity fund style categories described above. We also control for expense ratios, given that funds with high expense ratios tend to adjust risk (Kempf & Ruenzi, 2008), and we control for fund size, flows and turnover. As previous studies (e.g. Huang et al., 2011) suggest that risk-taking incentives shift according to return performance and fund age, we also control for those variables. Included, furthermore, as control variables, are funds' exposure to risk conditions—as given by the quarterly volatility and downside risk betas—and co-skewness, given that those variables may influence the way the fund deals with carbon risk. We include as further controls information on factor loadings, which reflect exposure by fund style to different sources of risks. Finally, we control for the unobserved heterogeneity of $CRS_{i,t}$ over time by including year-quarter fixed effects. To alleviate potential reverse causality concerns, the values of all independent

[11]This transformation is necessary to guarantee that the conditional expectation function takes values that fall within the range of the dependent variable, which naturally takes values between 0% and 100%. Although there are different approaches to dealing with fractional dependent variables (see, e.g. Cook et al., 2008; Papke & Wooldridge, 1996), the logit transformation is the simplest but also the most suitable approach for our data given that our sample—as shown in Figure 1—contains no top boundary observations and has a negligible probability of down boundary observations (only two equity funds have CRS values that equal 0).

variables are taken from the previous quarter-end. We estimate Equation 8 using ordinary least squares and standard errors are obtained from White cross-sectional error variances, with period clustering to account for both fund heteroskedasticity and correlation.

The results of estimating Equation 8 are presented in Table 2. Columns 1–4 report results for four specifications each of the single-management variables, whereas Column 5 presents evidence considering the four managerial variables together in the regression model.

TABLE 2 Managerial involvement and CRS in mutual funds

	(1)	(2)	(3)	(4)	(5)
Managerial variables					
Ownership$_{t-1}$	−0.008** (−3.67)				−0.007** (−3.55)
Team size$_{t-1}$		0.001 (0.47)			0.002 (0.96)
SRI$_{t-1}$			−0.071** (−4.78)		−0.071** (−4.80)
R_squared$_{t-1}$				−0.155** (−5.28)	−0.148** (−5.04)
Control variables					
LG	−0.595** (−7.00)	−0.605** (−7.12)	−0.594** (−6.99)	−0.623** (−7.33)	−0.602** (−7.09)
LB	−0.218** (−2.57)	−0.227** (−2.67)	−0.218** (−2.57)	−0.243** (−2.87)	−0.227** (−2.68)
LV	−0.123 (−1.45)	−0.132 (−1.56)	−0.128 (−1.51)	−0.144* (−1.69)	−0.132 (−1.56)
MG	−0.217** (−2.51)	−0.226** (−2.61)	−0.218** (−2.53)	−0.250** (−2.90)	−0.234** (−2.71)
MB	−0.044 (−0.51)	−0.053 (−0.61)	−0.048 (−0.56)	−0.077 (−0.90)	−0.064 (−0.74)
MV	0.005 (0.06)	−0.003 (−0.03)	0.001 (0.01)	−0.016 (−0.18)	−0.006 (−0.07)
SG	−0.361 (−1.54)	−0.368 (−1.57)	−0.368 (−1.57)	−0.429* (−1.83)	−0.413* (−1.77)
SB	−0.245** (−2.03)	−0.253** (−2.10)	−0.227* (−1.88)	−0.240** (−1.99)	−0.204* (−1.70)
Expense$_{t-1}$	−0.036 (−0.70)	−0.041 (−0.78)	−0.049 (−0.95)	−0.101* (−1.89)	−0.103* (−1.93)
Size$_{t-1}$	0.001 (0.51)	0.003 (1.33)	0.003 (1.13)	0.004 (1.40)	0.000 (0.07)
Flows$_{t-1}$	0.050** (2.28)	0.049** (2.24)	0.054** (2.46)	0.047** (2.14)	0.053** (2.41)
Turnover$_{t-1}$	0.000 (−1.33)	0.000 (−0.96)	0.000 (−1.24)	0.000 (−0.98)	0.000 (−1.60)
Return$_{t-1}$	−0.002* (−1.68)	−0.002 (−1.65)	−0.002* (−1.75)	−0.002 (−1.38)	−0.002 (−1.49)
Age$_{t-1}$	−0.001** (−3.77)	−0.001** (−3.71)	−0.001** (−3.63)	−0.001** (−3.28)	−0.001** (−3.18)
Volatility$_{t-1}$	−0.016** (−6.18)	−0.016** (−6.08)	−0.016** (−6.26)	−0.020** (−7.31)	−0.021** (−7.40)
β_{tail} t − 1	0.076** (9.19)	0.076** (9.17)	0.076** (9.18)	0.074** (8.94)	0.074** (8.95)
β_{VXTH} t − 1	0.043** (4.36)	0.043** (4.38)	0.043** (4.43)	0.027** (2.62)	0.028** (2.72)
Coskew$_{t-1}$	0.145** (5.08)	0.145** (5.06)	0.147** (5.14)	0.134** (4.69)	0.136** (4.78)
β_{M} t − 1	−0.104** (−5.35)	−0.104** (−5.35)	−0.104** (−5.34)	−0.028 (−1.10)	−0.030 (−1.18)
β_{SMB} t − 1	0.275** (10.63)	0.274** (10.60)	0.274** (10.60)	0.288** (11.05)	0.288** (11.07)
β_{HML} t − 1	0.427** (23.21)	0.426** (23.14)	0.430** (23.33)	0.416** (22.48)	0.421** (22.76)
β_{RMW} t − 1	−0.295** (−21.63)	−0.295** (−21.60)	−0.292** (−21.35)	−0.293** (−21.39)	−0.290** (−21.19)
β_{CMA} t − 1	0.475** (40.41)	0.475** (40.38)	0.477** (40.58)	0.472** (40.16)	0.475** (40.43)
β_{MOM} t − 1	−0.303** (−13.50)	−0.304** (−13.51)	−0.306** (−13.64)	−0.281** (−12.28)	−0.285** (−12.49)
Constant	−1.748** (−17.11)	−1.787** (−17.58)	−1.770** (−17.42)	−1.685** (−16.35)	−1.631** (−15.76)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8547	8547	8547	8547	8547
Adj. R^2	0.55	0.55	0.56	0.56	0.57

Notes: The table presents the least squares estimation of the parameters of the regression between the carbon risk score (CRS) as given by the log (CRS/(100 − CRS)) and managerial involvement measured by managerial ownership, team size, socially responsible investment (SRI) focus and active management, considering several control variables, including fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, gross returns, age, volatility, co-skewness, sensitivity to downside risk in the fund market (β_{tail}) and in the stock market (β_{VXTH}), factor loadings (β_M, β_{SMB}, β_{HML}, β_{RMW}, β_{CMA} and β_{MOM}) and quarterly fixed effects. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.
*Significance at the 10% level.
**Significance at the 5% level.

We find that funds headed by co-investing managers are associated with lower CRS levels than funds in which managers have less 'skin in the game'. Estimated coefficients for managerial ownership reported in Columns 1 and 5 are negative and significant at the 1% level, indicating that the marginal effects of an increase in ownership has an average impact of -0.007 on the dependent variable. This evidence is consistent with the hypothesis that managerial ownership dampens managers' incentives to take carbon risks, aligning their interests with the sustainability of the fund portfolio. Our results are in line with previous research supporting a lower risk associated with funds in which the managers are also owners (Evans, 2008; Fu & Wedge, 2011; Khorana et al., 2007; Ma & Tang, 2019), but in our case for the specific risk associated with carbon risk exposure in the mutual fund portfolio.

Columns 2 and 5 show that management team size has a negligible effect on the CRS of the fund. This evidence is consistent with the irrelevance of using a large managerial team to realign the fund portfolio with low carbon risk exposure. Not surprisingly, empirical evidence in Columns 3 and 5 confirms that SRI funds go hand in hand with funds with low CRS values, indicating that SRI funds exhibit lower carbon risk exposure, which is consistent with the SRI aims of funds and also with recent evidence reported by Nofsinger and Varma (2021). Finally, evidence in Columns 4 and 5 indicates that more active management (lower R-squared values) increases fund exposure to carbon risk, as the parameter estimate is negative and significant at the 1% level. This would suggest that managers that seek to profit from active trading assume more carbon risk in their portfolios than is assumed by the average fund portfolio.

As for the control variables, we find that the CRS is negatively impacted by fund age and volatility, indicating that younger and less volatile funds assume greater carbon risk. For downside risk, the empirical evidence shows that fund exposure to tail risk in the mutual fund sector has a positive and significant impact on the CRS, meaning that the CRS is reduced when fund exposure to tail risk increases. Similarly, fund exposure to tail risk in the financial market has a significant impact on the CRS. There is also evidence that co-skewness is positively related to the fund CRS, whereas the gross return performance is not associated with carbon risk. Our empirical estimates furthermore reveal that pricing factor betas, with the exception of the market risk factor, are related to carbon risk: Exposures to SMB, HML and CMA stock portfolios are positively associated with future values of the CRS, while fund exposures to diversified portfolios and contrarian stocks have a negative impact on the CRS. Fund flows are positively associated with the CRS, revealing that increasing fund's flows raises the portfolio CRS. Finally, we find that certain fund features, such as fund size, expense ratio and turnover, have no significant effects on carbon risk.

To sum up, our empirical evidence on fund portfolio carbon risk points to the following: (a) Risk is reduced with managers' involvement through ownership and the fund's SRI focus, and (b) risk is increased with active management, independently of the size of the management team. In addition, the carbon risk level is sensitive to certain pricing factors and volatility features of the fund.

3.2 | Robustness checks

We test for the robustness of the above results in different ways. First, we check the sensitivity of our evidence to model specification, running the regression model in Equation 8 using generalized least squares clustered at the fund level and checking for the sensitivity of standard errors to different variance–covariance matrix specifications. Those regressions result in similar evidence as reported in Table 2. Second, in checking the sensitivity of the results to the inclusion of different sets of control variables, the evidence regarding managerial variables remains the same. Finally, empirical results from running the regression model in Equation 8 using annual data for all variables for the years 2017 and 2018 point to similar evidence as reported in Table 2.

4 | DOES THE CRS AFFECT FUND PERFORMANCE?

In this section, we examine how portfolio CRS might affect fund performance along three dimensions: risk-adjusted returns, fund risks and fund flows.

4.1 | Risk-adjusted performance and the CRS

We examine whether the fund risk-adjusted performance—as given by the fund alphas—is sensitive to the fund portfolio CRS. Managing carbon risk may be at the cost of paying less attention to the portfolio return performance, or, alternatively, it may enhance performance as the result of a strict screening process that excludes underperforming companies with high carbon risk exposure. The mutual fund literature shows that SRI-oriented funds narrow the universe of stocks, and this is likely to negatively impact the performance of those funds (Renneboog et al., 2008). Other researchers have found that a firm's environmental or social commitments enhance performance (Basse & Mandaroux, 2021; Busch & Lewandowski, 2018; Dimson et al., 2015) and lower the cost of debt (Jung et al., 2016). We therefore test whether funds with high or low CRS ratings improve or weaken future risk-adjusted fund performance. We test for this effect by estimating the following regression model:

$$\mathrm{Alpha}_{i,t} = \omega + \beta \mathrm{CRS}_{i,t-1} + \theta \mathit{Controls}_{i,t-1} + \varepsilon_{i,t}, \tag{9}$$

where the dependent variable (*Alpha*) is the risk-adjusted return measure for fund *i* at year-quarter *t* obtained from Equation 1. The main independent variable is the portfolio CRS for mutual fund *i*. As for control variables, we include a similar set of variables as considered for Equation 8, as these are expected to affect risk-adjusted performance: fixed effects style dummies, expense ratio, fund size, fund flows, turnover, fund age, volatility, co-skewness and temporal fixed effects dummies. We also control for persistence in fund performance by including lagged values for *Alpha* and managerial ownership, team size, SRI focus and active management, given that those variables are likely to affect fund performance. In addition, we check the sensitivity of the effects of CRS on *Alphas* using different sets of control variables, lagged one-quarter to control for potential reverse causality concerns. We estimate Equation 9 using generalized least squares clustered at the fund level and obtain consistent standard errors from White cross-sectional error variances that account for both fund heteroskedasticity and correlation.

We present the estimation results of Equation 9 using different sets of control variables, as shown in Columns 1–5 of Table 3. Empirical tests from different regression specifications reveal that fund portfolios with low CRS ratings are associated with better risk-adjusted return performances in the following year-quarter, indicating that funds concerned about low carbon transition risks are more desirable to performance-chasing investors, given that the portfolio performance of those funds is better than that of funds with greater portfolio exposure to carbon risk. This evidence is consistent with that of Dimson et al. (2015), Ji et al. (2021) and Soler-Domínguez et al. (2021), who find a positive effect of sustainable stocks or mutual funds on performance.

As for the control variables, we find evidence of performance persistence over the quarterly horizon, as the lagged values of alpha are significant in all the specifications presented in Table 3. Congruent with previous research reporting that managerial ownership enhances performance (Evans, 2008; Khorana et al., 2007), we find that managerial ownership realigns decision-making and fund owner interests, as it is associated with better next-quarter risk-adjusted performance. Likewise, we find that the SRI character of the fund is unrelated to performance, whereas active management significantly improves performance (the estimated coefficient is significant

TABLE 3 Risk-adjusted fund performance and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	−0.001** (−6.40)	−0.001** (−7.52)	−0.001** (−8.37)	−0.001** (−6.48)	−0.001** (−5.74)
Control variables					
$Alpha_{t-1}$		0.076** (6.27)	0.083** (7.88)	0.135** (10.38)	0.106** (7.97)
$Ownership_{t-1}$			0.001** (3.99)		0.001** (3.78)
Team $size_{t-1}$			0.002 (1.15)		0.001 (0.62)
SRI_{t-1}			0.001 (0.39)		0.001 (0.60)
$R\_squared_{t-1}$			−0.046** (−17.27)		−0.049** (−16.82)
LG				0.013 (1.20)	0.005 (0.47)
LB				0.015 (1.37)	0.004 (0.37)
LV				0.019* (1.75)	0.008 (0.76)
MG				0.019* (1.67)	0.010 (0.89)
MB				0.009 (0.82)	−0.007 (−0.70)
MV				0.008 (0.70)	0.000 (−0.02)
SG				−0.053 (−0.63)	−0.078 (−0.91)
SB				−0.038 (−1.54)	−0.050** (−2.08)
$Expense_{t-1}$				−0.024** (−3.41)	−0.037** (−5.17)
$Size_{t-1}$				−0.001** (−2.22)	−0.001 (−1.56)
$Flows_{t-1}$				−0.007** (−2.31)	−0.005** (−2.01)
$Turnover_{t-1}$				−0.000** (−2.99)	−0.000* (−1.89)
Age_{t-1}				0.000 (−1.64)	0.000 (−0.29)
$Volatility_{t-1}$				0.002** (6.31)	0.001** (2.29)
$Coskew_{t-1}$				−0.019** (−4.18)	−0.023** (−5.28)
Constant	−0.033** (−21.56)	−0.029** (−18.66)	0.001 (0.53)	−0.031** (−2.41)	0.016 (1.24)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8,561	8561	8561
Adj. R^2	0.22	0.24	0.27	0.25	0.28

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between risk-adjusted performance (Alpha) and the carbon risk score (CRS) in Equation 9, considering the following lagged fund characteristics: risk-adjusted performance, managerial ownership, team size, socially responsible investment (SRI) focus, active management, fixed effects style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, age, volatility, co-skewness and quarterly fixed effects (FEs). *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.

and negative). Our evidence also shows that fund flows are negatively associated with the next year-quarter's risk-adjusted performance. Our results further indicate that there is a negative association of expense ratios and turnover with risk-adjusted performance in the next year-quarter. Finally, greater fund return volatility improves, whereas greater co-skewness weakens, risk-adjusted fund performance.

4.2 | Fund risk and the CRS

We study whether the fund risk level is sensitive to the fund portfolio CRS. One may reasonably argue that a fund concerned with portfolio risk management should also take into consideration any climate risks associated with the fund portfolio. Policy and legal regulations limiting carbon emissions—such as carbon taxes and other compliance measures—are judiciously expected to impact the profitability and risk of firms, which, in turn, could impair their financial position. We therefore test for the effect of the fund portfolio CRS on portfolio risk using a similar regression model as in Equation 9, where the dependent variable now measures fund portfolio risk:

$$\mathrm{Risk}_{i,t} = \omega + \beta \mathrm{CRS}_{i,t-1} + \theta \mathit{Controls}_{i,t-1} + \varepsilon_{i,t}. \tag{10}$$

Fund risk (*Risk*) is measured along four dimensions: fund returns volatility, exposure to market risk, co-skewness and exposure to downside risk. Control variables include fixed effects style dummies, expense ratio, fund size, flows, turnover, fund age, risk-adjusted performance and temporal fixed effects dummies. We also include lagged values of risk to control for persistence, as well as information on managerial ownership, team size, SRI focus and active management, given that those variables are likely to affect fund risks. Control variables are

TABLE 4 Fund return volatility and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	0.042** (8.10)	0.036** (8.44)	0.036** (8.46)	0.060** (13.26)	0.057** (12.71)
Control variables					
$\mathrm{Volatility}_{t-1}$		0.301** (18.41)	0.264** (16.91)	0.281** (16.72)	0.290** (16.88)
$\mathrm{Ownership}_{t-1}$			−0.012** (−2.24)		−0.016** (−2.90)
$\mathrm{Team\ size}_{t-1}$			−0.228** (−4.94)		−0.137** (−3.19)
SRI_{t-1}			−0.194** (−3.86)		−0.230** (−4.72)
$\mathrm{R\_squared}_{t-1}$			0.786** (8.82)		1.142** (12.51)
LG				0.405 (0.82)	0.653 (1.25)
LB				−0.263 (−0.53)	0.034 (0.07)
LV				−0.490 (−1.00)	−0.230 (−0.45)
MG				0.101 (0.20)	0.335 (0.64)
MB				−0.230 (−0.46)	0.176 (0.34)
MV				−0.493 (−1.00)	−0.299 (−0.58)
SG				1.439 (1.40)	2.108* (1.91)
SB				2.502** (3.93)	2.976** (4.56)
$\mathrm{Expense}_{t-1}$				1.489** (6.97)	1.769** (8.06)
Size_{t-1}				0.009 (0.95)	0.002 (0.21)
Flows_{t-1}				0.105 (1.30)	0.110 (1.34)
$\mathrm{Turnover}_{t-1}$				0.002** (6.18)	0.002** (5.50)
Age_{t-1}				0.005** (3.77)	0.004** (3.03)
Alpha_{t-1}				2.405** (6.17)	3.269** (7.87)
Constant	6.835** (112.91)	5.158** (53.25)	6.806** (63.89)	4.278** (7.89)	3.423** (5.90)
Year-quarter FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8561	8561	8561
Adj. R^2	0.47	0.49	0.57	0.61	0.62

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between fund volatility and the carbon risk score (CRS) in Equation 10, considering the following lagged fund characteristics: return volatility, managerial ownership, team size, socially responsible investment (SRI) focus, active management, fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, age, risk-adjusted performance (alpha) and quarterly FEs. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.

*Statistical significance at the 10% level.

**Statistical significance at the 5% level.

lagged one-quarter to mitigate potential reverse causality concerns and the sensitivity of the effects of the CRS on risk is checked using different sets of control variables.

Table 4 presents empirical results on the effects of the CRS on fund return volatility. For five specifications (see Columns 1–5) with different sets of control variables, we find that the CRS of the fund is positively and significantly associated with portfolio returns risk in the next year-quarter, that is, neglecting carbon risk is reflected in greater volatility. Consequently, managing carbon transition risks has favourable effects on the volatility of the fund portfolio. We also find evidence of volatility persistence, as the estimate of the lagged volatility parameter is positive and significant in different regression specifications. As for the managerial control variables, the estimated coefficients on managerial ownership are negative and significant at the 5% level, suggesting that the fund portfolio risk reduces as managerial ownership increases—a result corroborating those reported for previous empirical studies (Ma & Tang, 2019). Similarly, the coefficients for the size of the managerial team and the SRI character of the fund are negative and significant at the 1% level, pointing to a reduction in portfolio risk for a larger management team at the helm and for an SRI focus. Moreover, we find consistent evidence on the effect of active management on fund portfolio volatility: As active management increases, portfolio return volatility falls. Regarding control variables, we find that the fund risk level increases with expense ratio, turnover, fund age and risk-adjusted returns but is not affected by fund flows and fund size.

Table 5 shows that exposure of the fund portfolio to market risk as given by $\beta_{i,VIX}$ is positively related to the CRS. Coefficient estimates from different specifications in Columns 1–5 are positive and significant at the 1% level, indicating that the portfolio CRS level is positively associated with the fund's exposure to the next year-quarter's market volatility. Thus, unmanaged carbon risk makes the portfolio

TABLE 5 Fund exposure to market volatility (β_{VIX}) and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	0.001** (2.70)	0.001** (3.44)	0.001** (3.62)	0.001** (3.35)	0.001** (3.81)
Control variables					
β_{VIX} t − 1		−0.024** (−4.58)	−0.026** (−4.36)	−0.031** (−4.17)	−0.043** (−5.54)
$Ownership_{t-1}$			−0.001* (−1.88)		0.000 (−0.01)
$Team\ size_{t-1}$			−0.003 (−1.35)		−0.004* (−1.84)
SRI_{t-1}			−0.006** (−2.36)		−0.003 (−1.08)
$R\_squared_{t-1}$			0.056** (13.46)		0.082** (17.07)
LG				−0.054* (−1.94)	−0.045 (−1.66)
LB				−0.061** (−2.20)	−0.048* (−1.78)
LV				−0.057** (−2.04)	−0.046* (−1.69)
MG				−0.035 (−1.26)	−0.024 (−0.87)
MB				−0.032 (−1.14)	−0.011 (−0.39)
MV				−0.026 (−0.92)	−0.018 (−0.66)
SG				−0.072 (−0.73)	−0.031 (−0.31)
SB				0.008 (0.23)	0.040 (1.16)
$Expense_{t-1}$				−0.034** (−2.39)	−0.015 (−1.04)
$Size_{t-1}$				0.000 (0.88)	0.000 (0.73)
$Flows_{t-1}$				0.000 (0.20)	−0.011** (−2.28)
$Turnover_{t-1}$				0.000** (2.95)	0.000** (2.87)
Age_{t-1}				0.000** (2.34)	0.000 (1.17)
$Alpha_{t-1}$				−0.066** (−4.78)	−0.106** (−7.48)
Constant	−0.035 (−16.93)	−0.038** (−15.94)	−0.075** (−16.43)	0.003 (0.10)	−0.067** (−2.26)
Temporal FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8561	8561	8561
Adj. R^2	0.08	0.09	0.11	0.11	0.15

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between fund exposure to market volatility (β_{VIX}) and the carbon risk score (CRS), considering the following lagged fund characteristics: fund exposure to market volatility, managerial ownership, team size, socially responsible investment (SRI) focus, active management, fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, age, alpha and quarterly FEs. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.

fund more sensitive to market risk. Our evidence also shows reversal effects in the sensitivity of the fund portfolio to market risk. In addition, coefficient estimates for the control variables show that the fund's exposure to market volatility reduces with active management, increases with turnover and is negatively related to portfolio risk-adjusted returns.

We present evidence on the effects of the CRS on co-skewness in Table 6. As shown in Columns 4–5, the estimated coefficients for the CRS are negative and significant, which indicates that increasing the CRS of the fund portfolio reduces co-skewness—a desirable portfolio feature for investors. Note, however, that this result holds only for the regression specification with the most complete set of control variables. As for the control variables, we find that the estimated coefficient for risk-adjusted returns is positive and significant, indicating that funds with higher alphas have portfolios with greater co-skewness.

Tables 7 and 8 report evidence on the effect of the fund CRS on fund portfolio sensitivity to downside risk in the mutual fund and in financial markets, given by the tail risk loadings, $\beta_{i,tail}$ and $\beta_{i,VXTH}$, respectively. Coefficient estimates in Columns 1–5 of Table 7 for the relationship between the CRS and $\beta_{i,tail}$ are negative and significant at the 1% level, indicating that there is a negative relationship between the fund CRS and the tail risk of the fund portfolio and suggesting that unmanaged carbon risk reduces fund portfolio sensitivity to tail risk in the mutual fund market; contrarily, reducing the carbon transition risk increases the fund portfolio sensitivity to tail risk. Similarly, negative and significant estimates in Columns 1–5 of Table 8 for the effects on the CRS on fund exposure to market downside risk indicate that managing carbon transition risk has unfavourable effects on market tail risk. Taken together, managing carbon risk has unfavourable effects on the tail risk of the fund portfolio. Evidence for the control variables suggests that the risk-adjusted returns of the fund portfolio are

TABLE 6 Co-skewness and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	−0.000 (0.56)	−0.000 (0.54)	−0.000 (−0.40)	−0.001** (−5.34)	−0.001** (−5.15)
Control variables					
$Co\text{-}skewness_{t-1}$		0.005 (0.67)	0.006 (0.68)	0.002 (0.27)	0.003 (0.36)
$Ownership_{t-1}$			0.000 (0.33)		0.000 (−0.27)
$Team\ size_{t-1}$			0.001 (0.38)		0.000 (−0.06)
SRI_{t-1}			0.000 (0.13)		0.002 (0.48)
$R\_squared_{t-1}$			0.001 (0.27)		0.008 (1.64)
LG				0.007 (0.26)	0.008 (0.31)
LB				0.024 (0.93)	0.026 (0.99)
LV				0.036 (1.41)	0.038 (1.47)
MG				0.007 (0.26)	0.008 (0.31)
MB				0.045* (1.75)	0.048* (1.86)
MV				0.034 (1.32)	0.035 (1.35)
SG				0.042 (0.50)	0.048 (0.57)
SB				−0.011 (−0.32)	−0.007 (−0.19)
$Expense_{t-1}$				−0.006 (−0.46)	0.000 (−0.02)
$Size_{t-1}$				0.000 (−0.76)	−0.001 (−0.79)
$Flows_{t-1}$				0.003 (0.51)	0.003 (0.55)
$Turnover_{t-1}$				0.000 (−1.46)	0.000 (−1.52)
Age_{t-1}				0.000 (0.12)	0.000 (−0.03)
$Alpha_{t-1}$				0.142** (7.49)	0.143** (7.52)
Constant	−0.025 (−11.15)	−0.025** (−10.99)	−0.027** (−5.89)	−0.021 (−0.72)	−0.029 (−0.99)
Temporal FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8561	8561	8561
Adj. R^2	0.09	0.09	0.10	0.12	0.12

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between fund co-skewness and the carbon risk score (CRS), considering the following lagged fund characteristics: co-skewness, risk-adjusted performance, managerial ownership, team size, socially responsible investment (SRI) focus, active management, fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, age, alpha and quarterly FEs. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.

*Statistical significance at the 10% level.

**Statistical significance at the 5% level.

TABLE 7 Fund exposure to fund market downside risk (β_{tail}) and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	-0.001^{**} (-3.55)	-0.001^{**} (-3.91)	-0.001 (-4.05)	-0.001^{**} (-3.13)	-0.001^{**} (-3.17)
Control variables					
β_{tail} $t-1$		-0.002^{**} (-1.40)	-0.003 (-1.35)	-0.001 (0.26)	-0.001 (-0.30)
$Ownership_{t-1}$			0.000 (-0.56)		0.000 (-0.56)
$Team\ size_{t-1}$			-0.002 (-1.19)		-0.003 (-1.23)
SRI_{t-1}			-0.001 (-0.58)		0.001 (0.22)
$R\_squared_{t-1}$			0.001 (0.15)		-0.005 (-0.74)
LG				-0.008 (-0.38)	-0.007 (-0.34)
LB				-0.001 (-0.06)	-0.001 (-0.02)
LV				0.006 (0.27)	0.007 (0.32)
MG				0.003 (0.16)	0.005 (0.22)
MB				0.000 (-0.02)	0.000 (0.01)
MV				0.014 (0.64)	0.015 (0.70)
SG				-0.013 (-0.12)	-0.017 (-0.15)
SB				-0.094^{**} (-2.17)	-0.096^{**} (-2.20)
$Expense_{t-1}$				-0.013 (-0.95)	-0.016 (-1.14)
$Size_{t-1}$				-0.001 (-1.07)	-0.001 (-1.08)
$Flows_{t-1}$				-0.008 (-1.33)	-0.008 (-1.33)
$Turnover_{t-1}$				0.000 (-0.30)	0.000 (-0.21)
Age_{t-1}				0.000 (1.05)	0.000 (1.04)
$Alpha_{t-1}$				0.046^{**} (2.86)	0.048^{**} (2.88)
Constant	0.076^{**} (32.15)	0.076^{**} (33.36)	0.079^{**} (18.16)	0.097^{**} (4.02)	0.105^{**} (4.10)
Temporal FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8561	8561	8561
Adj. R^2	0.12	0.11	0.11	0.12	0.12

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between fund exposure to fund market downside risk (β_{tail}) and the carbon risk score (CRS), considering the following lagged fund characteristics: fund exposure to fund market downside risk, managerial ownership, team size, socially responsible investment (SRI) focus, active management, fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, age, risk-adjusted performance and quarterly FEs. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.

positively associated with fund portfolio sensitivity to tail risk; that is, increasing risk-adjusted portfolio returns raises tail risk loadings. Additionally, we find that management fees, fund flows and turnover are unrelated to tail risk loadings. Contrary to some extant literature that links tail risk with managerial variables (e.g. Huang et al., 2011; Karagiannis & Tolikas, 2019), we find that managerial variables, with the exception of active management for market downside risk, are not significantly related to tail risk loadings. Overall, our evidence points to the fact that funds managing carbon risk are more sensitive to tail risk.

4.3 | Fund flows and the CRS

We examine the effect of carbon transition risk management on net fund flows. Arguably, the CRS is likely to influence investment decisions, and those decisions should be consistently reflected in fund flows. Thus, the CRS is likely to have effects on the performance–flow relationship so that a rising portfolio CRS should discourage both risk-adverse investors and environmentally conscious investors, with the corresponding detrimental effects on fund flows. Ceccarelli et al. (2021) report that discrete information on sustainability and on low carbon designations have positive effects on fund flows. However, Reboredo and Otero (2021) document that only continuous information on carbon risk is reflected in fund flows. To test the relationship between the CRS and fund flows, we estimate the following regression model:

$$Flows_{i,t} = \omega + \beta CRS_{i,t-1} + \theta Controls_{i,t-1} + \varepsilon_{i,t}, \tag{11}$$

where *Flows* are net fund flows as per Equation 7. As control variables we include variables that have been considered in the

TABLE 8 Fund exposure to market downside risk and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	−0.006** (−7.40)	−0.008** (−8.51)	−0.014** (−15.10)	−0.001** (−7.29)	−0.013** (−9.65)
Control variables					
β_{VXTH} t − 1		0.152** (11.95)	0.135** (9.45)	0.157** (11.94)	0.149** (10.20)
$Ownership_{t-1}$			−0.001 (−0.87)		−0.001 (−0.44)
Team $size_{t-1}$			−0.005 (−0.63)		−0.002 (−0.22)
SRI_{t-1}			0.001 (0.07)		0.002 (0.18)
$R\_squared_{t-1}$			−0.619** (−28.98)		−0.615** (−25.09)
LG				0.068 (0.64)	0.026 (0.23)
LB				0.103 (0.96)	0.042 (0.37)
LV				0.096 (0.90)	0.034 (0.30)
MG				0.008 (0.08)	−0.070 (−0.61)
MB				0.190* (1.75)	0.061 (0.53)
MV				−0.007 (−0.06)	−0.055 (−0.49)
SG				0.501** (2.12)	0.161 (0.74)
SB				0.206 (1.34)	0.049 (0.32)
$Expense_{t-1}$				0.043 (0.78)	−0.110* (−1.91)
$Size_{t-1}$				0.000 (−0.22)	0.000 (0.16)
$Flows_{t-1}$				−0.020 (−1.10)	−0.018 (−0.99)
$Turnover_{t-1}$				0.000* (−1.86)	0.000 (−1.26)
Age_{t-1}				0.000 (−1.54)	0.000 (−0.36)
$Alpha_{t-1}$				0.299** (4.88)	0.609** (8.75)
Constant	0.182** (17.91)	0.180** (16.80)	0.680** (32.33)	0.120 (1.08)	0.678** (5.67)
Temporal FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8561	8561	8561
Adj. R^2	0.10	0.14	0.28	0.17	0.27

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between fund exposure to fund market downside risk (β_{VXTH}) and the carbon risk score (CRS) and the following lagged fund characteristics: risk-adjusted performance, managerial ownership, team size, socially responsible investment (SRI) focus, active management, fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB), expense ratio, size, flows, turnover, age, volatility, co-skewness, fund factor loadings and quarterly FEs. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.

literature (e.g. El Ghoul & Karoui, 2017; Spiegel & Zhang, 2013) to examine the flow–performance relationship; specifically, we control for flow persistence by considering lagged flow values (e.g. Del Guercio & Tkac, 2001; Fant & O'Neal, 2000) and also include risk-adjusted past performance (*Alpha*) and fund return volatility, given that investor decisions largely depend on past performance (past performance and flows are therefore likely to be positively linked). Moreover, we consider information on fees, fund size, fund age and turnover, which are expected to affect future net fund flows (Spiegel & Zhang, 2013). We also include the SRI nature of the fund—as these funds are less sensitive to performance than conventional funds (El Ghoul & Karoui, 2017; Renneboog et al., 2011)—and information on managerial ownership, team size and fund activity level. Finally, we control for unobserved heterogeneity by cross section and over time by including fixed effects style dummies, defined according to the nine Morningstar equity fund style categories (as described earlier) and year-quarter fixed effects. To mitigate potential reverse causality concerns, control variables are lagged one quarter. We estimate Equation 11 using generalized least squares clustered at the fund level and obtain consistent standard errors from White cross-sectional error variances that account for both fund heteroskedasticity and correlation.

Table 9 presents the estimation results of Equation 11. From the different specifications shown in Columns 1–5, it can be observed that fund flows respond negatively and significantly to the portfolio CRS. This evidence suggests that an increased fund portfolio CRS has detrimental effects on fund flows—a result that is consistent with previous research (e.g. Reboredo & Otero, 2021; Spiegel & Zhang, 2013) on the role of risk on fund flows, although note that we report evidence specifically for carbon transition risk. Therefore, our evidence suggesting that

TABLE 9 Fund flows and CRS

	(1)	(2)	(3)	(4)	(5)
CRS_{t-1}	−0.001* (−4.81)	−0.001* (−4.29)	−0.001* (−2.31)	−0.001** (−3.05)	−0.001** (−3.13)
Control variables					
$Flows_{t-1}$		0.248** (9.74)	0.243** (9.55)	0.222** (8.78)	−0.001** (−3.13)
$Alpha_{t-1}$		0.226** (8.88)	0.234** (8.95)	0.311** (8.85)	0.221** (8.74)
$Volatility_{t-1}$				0.004** (4.42)	0.315** (8.96)
$Expense_{t-1}$				−0.158** (−6.30)	0.004** (4.13)
$Size_{t-1}$				−0.009** (−6.78)	−0.166** (−6.42)
Age_{t-1}				−0.001** (−8.57)	−0.008** (−6.55)
$Turnover_{t-1}$				0.000 (0.40)	−0.001** (−8.32)
SRI_{t-1}			0.014* (1.84)		0.000 (0.60)
$Ownership_{t-1}$			0.003 (1.19)		0.012* (1.69)
Team $size_{t-1}$			0.004 (0.92)		0.001 (0.39)
$R\_squared_{t-1}$			−0.025** (−2.59)		0.003 (0.68)
LG			−0.001 (−0.01)	0.026 (0.36)	−0.020** (−2.03)
LB			−0.009 (−0.12)	0.017 (0.24)	0.018 (0.26)
LV			−0.014 (−0.19)	0.011 (0.16)	0.009 (0.12)
MG			−0.025 (−0.34)	0.006 (0.09)	0.005 (0.06)
MB			−0.024 (−0.33)	0.002 (0.03)	−0.001 (−0.01)
MV			−0.021 (−0.29)	0.006 (0.09)	−0.008 (−0.11)
SG			0.002 (0.03)	0.057 (0.74)	0.001 (0.01)
SB			−0.039 (−0.52)	0.001 (0.01)	0.043 (0.56)
Constant	0.018** (5.03)	0.021** (5.80)	0.037 (0.50)	0.221** (2.79)	−0.015 (−0.21)
Temporal FEs	Yes	Yes	Yes	Yes	Yes
# Obs.	8561	8561	8561	8561	8561
Adj. R^2	0.001	0.08	0.09	0.11	0.11

Notes: The table presents the generalized least squares estimation of the parameters of the regression model between net fund flows and the carbon risk score (CRS), considering the following lagged fund characteristics: CRS, net fund flows, risk-adjusted portfolio returns (alpha), return volatility, expense ratio, size, age, turnover, socially responsible investment (SRI) focus, managerial ownership, team size, active management (R-squared), fixed effects (FEs) style fund investment (LG, LB, LV, SG, SB, SV, SG, SB) and quarterly FEs. *T*-statistics (in parenthesis) are computed using White cross-sectional error variances with period clustering to account for both fund heteroskedasticity and correlation.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.

investors are sensitive to the portfolio carbon transition risk is coherent with evidence reported above that points to the fact that higher CRS ratings reduce risk-adjusted returns and consistently lessen fund flows. Looking at the control variables, we find evidence of persistence in fund flows as shown by the statistically significant coefficients for lagged flows, although it can be observed that the sign of the lagged effects changes through different specifications. We also find that fund flows positively respond to lagged fund performance, consistent with the fact that improvements in performance attract the interest of performance-chasing investors and reward the funds performing best in terms of flows. We find that returns volatility increases fund flows and also that fund flows are negatively related to fund size, suggesting diseconomies of scale (i.e. funds face difficulties as they grow larger). Likewise, fund SRI policy has some positive effect on fund flows. Finally, fund age has a negative impact on fund flows, whereas the remaining control variables have no effect on fund flows.

4.4 | Robustness checks

We report a battery of robustness tests for the above-described evidence on portfolio CRS and fund performance. We re-estimate Equation 9 using alternative measures of fund return performance, namely, alphas from the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model and the market return model. The coefficient estimates for the CRS using all these performance measures are negative, significant and of a similar magnitude as the estimates presented in Table 3. In addition, for fund portfolio raw returns, coefficient estimates of the CRS are negative and significant across all specifications, with the economic magnitude of the coefficients ranging from −0.07 to −0.12 and with robust *t*-statistics of −4.24 and −8.37, respectively. Thus, our finding of a deterioration in fund return performance as the CRS increases is robust to alternative performance measures.

We repeat the analysis in Table 4 using alternative measures of fund return volatility, including quarterly standard deviation of daily returns and quarterly idiosyncratic volatilities (see Ang et al., 2006) computed as the standard deviation of the daily residuals from the regression model in Equation 1. Using those measures, estimated coefficients of the CRS are positively significant and of a similar magnitude as the coefficients reported in Table 4.

In relation to the robustness of our evidence on the impact of the CRS on fund exposure to market tail risk, we consider different levels of confidence for the ES values in Equation 4, including 1% and 10%, finding that the impact of the CRS on tail beta loading is negatively significant and of a similar magnitude as reported in Table 7. We also re-estimate the sensitivity of each fund to downside risk by considering the value at risk in Equation 4 instead of the ES, re-estimating the CRS coefficients as in Table 7. The empirical evidence confirms that increased CRS ratings reduce tail risk loading.

Finally, we test the sensitivity of the results reported in Tables 3–9 to model specification as follows: (a) by running different regressions using alternative specifications for the variance–covariance residual matrix; (b) by estimating standard errors under different specifications to test for the robustness of parameter significance; and (c) by using different combinations of control variables. Evidence from those estimations confirms the results reported in Tables 3–9.

5 | CONCLUSIONS

Although the transition to a decarbonized economy is likely to cause severe disruption and potential losses for companies operating with business models that rely directly or indirectly on carbon-intensive activities, it also brings new investment opportunities in low carbon businesses. Assessing how mutual funds are positioned relative to this transition risk is of utmost importance for investors facing a trade-off between short-term gains from carbon-intensive businesses and potential re-valuation of low-carbon assets in a decarbonized economy. We investigate whether managerial ownership, team size, an SRI focus and active management shape low carbon risk management of fund portfolios. We also analyse how low carbon risks impact on fund performance, including risk-adjusted returns, portfolio volatility, tail risk and fund flows.

For a sample of US domestic equity mutual funds quarterly rated with a CRS by Morningstar in 2017 and 2018, we find that the fund portfolio CRS reduces with managerial involvement through ownership and with an SRI focus. However, CRS ratings are not affected by managerial team size and are intensified by active management. Regarding fund performance, risk-adjusted return performance is reduced, and fund portfolio volatility surges when the portfolio CRS increases. However, lower CRS ratings are also associated with higher exposure to tail risk. In examining the relationship with fund flows, these are reduced when the CRS increases, indicating that investors are sensitive to carbon transition risks. Our results point to the fact that fund flows increase when the CRS falls. Furthermore, the fund SRI policy reduces CRS, which in turn increases flows of SRI funds. Overall, our evidence indicates that managerial involvement and decision-making shape low carbon transition risks and that managing those risks has favourable effects on fund performance and flows. Our findings further highlight the fact that the restructuring of fund portfolios according to environmental criteria does not have detrimental effects on portfolio performance and attracts investment flows.

Our empirical evidence is regionally circumscribed to the United States, where mutual fund managers have a specific environmental consciousness that might differ from that of managers based in other regions. Examining how fund managers in other economic areas such as Europe or Asia respond to low carbon transition risk information is an interesting topic to address, which we leave for future research.

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APPENDIX A

This appendix shows the results of the interval regression estimates for managerial investment to convert managerial investment intervals into a pseudo-continuous variable. Consider (unobserved) managerial investment y_i* as given by

$$y_i^* = X_i'\beta + \varepsilon_i, \quad \text{(A1)}$$

where X_i is a vector that includes explanatory variable related to fund i characteristics. For a given (normal) distribution of ε_i, we obtain parameter estimates by maximizing the log-likelihood function:

$$\ell_i(\beta,\sigma) = \ln P(m_i < y_i^* \le M_i) = \ln\left[\Phi\left(\frac{M_i - X_i'\beta}{\sigma}\right) - \Phi\left(\frac{m_i - X_i'\beta}{\sigma}\right)\right], \quad \text{(A2)}$$

using numerical procedures. Table A1 reports parameter estimates for different variables used in the regression estimates along with the bootstrap standard errors and t-statistics.

TABLE A1 Estimates for managerial investment

	Parameter	Std. error	*T*-statistic
LG	239631.5**	69832.93	3.43
LB	134262.8*	69731.66	1.93
LV	102080.2	69521.83	1.47
MG	155137.6**	72141.31	2.15
MB	64064.76	70536.4	0.91
MV	102612.5	69439.94	1.48
SG	−37339.91	71263.05	−0.52
SB	−190202.7**	93706.39	−2.03
SRI	−3098.961	26513.51	−0.12
Age	739.9285	725.1647	1.02
Turnover	−1059.083**	185.1609	−5.72
Size	84266.94**	4135.985	20.37
Return_{t-1}	−37.08912	443.1477	−0.08
Constant	−1358170**	108985.8	−12.46

*Significance at the 10% level.
**Significance at the 5% level.