Investors' Behaviour: Carbon Risk Score and Climate Risk Media Visibility

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Abstract

This paper examines whether US mutual fund investors are aware of the carbon risk score of their portfolios and the influence that media spread on climate news has on their money flows. The study is carried out by analyzing 1,352 US domestic equity funds during the period 1999-June 2023. Results show that climate news affect fund investor behavior. Specifically, the greater extent to which climate risk and uncertainty issues are addressed in the leading newspapers negatively affects investor flows in funds with high exposures to carbon risks. Conversely, we find a positive impact on low-carbon risk funds, especially in more recent periods. This evidence remains even after controlling for fund size, financial performance and other variables that could drive investor flows.

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1. Introduction

Socially responsible mutual funds have exhibited a clearly increasing tendency over the recent years, linked to the growing interest in social matters that society in general and mutual fund investors in particular have presented. Concretely, according to Klinkowska and Zhao (2023), ESG investment under professional management in US has grown from \$3.1 trillion (out of \$25.2) in 2010 to \$17.1 trillion (out of \$51.4) in 2020.[1] This paper, similarly to other works in the recent literature, shows that investors are involved not only in financial performance but also search for sustainability performance.

In this context, while these studies analyze that investment flows are generally affected by sustainability ratings, in this paper we try to shed a more detailed light on this influence. Concretely, our aim is examining the affection of each pillar given that; for instance, climate risks are considerably different compared to those observed in the remaining pillars.

Some studies analyze investors' preferences for SRI products (see, e.g., Renneboog *et al*., 2011; Barber *et al*., 2021; Bauer *et al*., 2021). However, these studies lack a deep consideration of the environmental dimension. Climate change entails risks for the value of firms due to the impact of natural disasters on the firm activity and value of the assets or due to the changes in consumer preferences or in regulatory policies limiting carbon emissions (see, e.g., Reboredo and Otero, 2021). It is important to examine whether investors are becoming aware of climate-related risks. Following another strand of the related literature, Berrone *et al*. (2017) and Chiu and Sharfman (2009) argue that companies increase their commitment to corporate social responsibility because of a higher public attention.

For that reason, in this paper we study how US mutual fund investors respond to climate-related risks associated with the transition to a low-carbon economy by using the carbon risk score (CRS) and how the investor flow-CRS relationship can be affected by the media spread on climate risk news. Our aim is justified because despite the growing importance of environmental risks, little is known about the factors that drive investors to mitigate these risks. Hence, we find a gap in the literature regarding the interest to shed

[1] Data provided by USSIF (US Sustainable Investment Forum)

additional light on the potential influence on investment decisions provoked by the increase of the media interest on climate risk issues.

Following this objective, and given that we do not have information on funds' CRS in earlier periods, we first examine fund persistence on the level of CRS achieved by mutual funds using two-way tables (Malkiel, 1995). Results show that the level of CRS is extremely persistent on a quarterly basis. This way, more than the 80% of the sample examined remains in the same quintile level during two consecutive periods (98% in case of considering the same and the contiguous quintile levels). This evidence on persistence allows us to infer the level of CRS in periods when funds existed but did not report any information on this characteristic.

Next, we start checking the media influence in examining the evolution of the total net assets managed by funds with different exposures to carbon risk. Concretely, we find that funds with the lowest carbon risks have significantly increased their importance in terms of TNA, contrasting markedly the behaviour of the highest carbon risk funds. Then, we try to observe if funds with different scores are affected by the extent that climate issues are addressed in newspapers. Along these lines, we find that an increase in the media visibility about climate risk issues during the previous months entails an increase in the assets managed by Low-carbon risk funds, and a decrease in the size of funds with higher carbon risk exposures. As commented above, one potential explanation relates to investor decisions, since their investments and divestments directly affect fund assets.

Moreover, we firstly control for fund size and fund returns, since both variables directly affect investor flows. On the one hand, since the computation of net cash flows rely on the scale of total net assets under fund management. On the other hand, given the positive flow-performance relationship shown in previous studies (Ferreira et al., 2012; Wang et al., 2018). To examine whether the relation between fund CRS and investor flows was affected by media attention to climate issues, we focus these analyses on two sub-periods related to lower and greater climate risk visibility in US newspapers, as proxied by the Climate Policy Uncertainty Index, or CPU (Gavriilidis, 2021).

Regarding fund flows controlled by size and CPU relevance, we do not find overall differences between funds with Low and High carbon risk scores. However, we find that High carbon risk funds receive significantly scarcer flows in the more recent period, precisely when CPU reaches more importance.

We also wonder if the relationship between fund flows and past financial performance has maintained similar patterns along time. Regarding this issue, we find that fund with High carbon risk scores achieved more flows than those with lows scores and similar financial performance in the first subperiod. However, this relation has changed in the recent years when Low carbon risk score funds obtain significantly higher funds.

Finally, we carry out additional analyses to disentangle the influence of CPU on fund flows. To do this, we differ among funds with High carbon risk scores and funds with Low CRS records. When we consider the influence of CPU on net cash flows, results indicate that the Low carbon risk score funds achieve higher net flows when the media spread on climate news increases. In distinguishing between inflows and outflows, we observe that the aforementioned net flow behaviour mainly results from lower redemptions suffered by Low carbon risk score funds in increasing CPU scenarios.

This paper contributes to the literature that examines how fund investors respond to climate-related risks associated with the transition to a low carbon economy through the analysis of investment flows attracted by funds depending on their carbon risk score. Reboredo and Otero (2021) demonstrate that US fund investors allocate relatively more money to funds with lower Carbon Risk Score (CRS) values. They point that the CRS metric conveys specific information that reinforces the positive effect of sustainability and SRI ratings on fund flows previously documented by Ammann et al. (2019) and Hartzmark and Sussman (2019). Ceccarelli *et al*. (2023) also show that low-carbon mutual funds have improved flows compared to non-labelled funds.

The study also contributes to the literature on sustainable investments. Some studies analyse investors' preferences for SRI products (see, e.g., Renneboog et al., 2011; Bauer et al., 2018 and Barber et al., 2019) but without a deep consideration of the climate risk dimension. Moreover, the study also contributes to the literature that examines the influence of public attention to environmental issues on investment decisions. Specifically, this is the first study that examines the influence of the Climate Policy Uncertainty (CPU index hereafter) on investment flows. Hence, this paper reinforces the idea that climate-related news impact mutual fund investment decisions with the Carbon Risk Score along with the CPU index.

The rest of the study is organized as follows: In Section 2, we describe the data. Section 3 shows the empirical analyses and Section 4 concludes.

2. Data

Fund data are provided by Morningstar database. This includes fund identifiers, inception date, and data on monthly net returns, total net assets, turnover ratio and net expense ratio, among other characteristics. This database also includes information on funds' carbon risk score (CRS) on a quarterly frequency from 2017 on. Fund score on carbon risk is a weighted average for the carbon risk score attributed to the assets held in fund portfolio.

Our initial sample comprises 13,111 US domestic fund share classes investing mainly in equities during the period January 1999-June 2023. This sample is free of survivorship bias since it includes both surviving and non-surviving funds. We group all the share-classes related to the same fund, and exclude index funds and funds of funds from the sample. Fund observations with less than 18 months since inception and funds managing less than 15 million dollars are also dropped from the sample in order to avoid potential incubation biases. These treatments lead to include 2,480 different actively-managed equity funds in the sample.

Given that we are interested in assessing investor behavior in relation to fund carbon risks, we additionally exclude funds with no information on CRS from the analyses (mostly, funds that were terminated before 2017), reducing the final sample to 1,352 mutual funds. Table 1 shows some descriptive statistics about the US mutual funds examined.

(Insert Table 1)

As shown, the average fund experienced an annualized return of 8.69%, and reported 1,419 million dollars under management. Given that we focus on active funds, their annual expenses and turnover ratios were relatively higher (averages of 1.38% and 93.80%, medians of 1.3312 and 71.50%, respectively) than those that we could find among passively-managed index funds. More importantly, funds are linked to an average CRS of 9.62 (median of 9.35). Nonetheless, funds in the sample differ in their exposure to carbon risks, given the value that the standard deviation yields for this variable.

Additionally, the study uses as a proxy for the media visibility on climate issues the US Climate Policy Uncertainty (CPU) Index developed by Gavriilidis (2021). This index is based on the number of articles related to climate or carbon dioxide issues, policy or regulation, and uncertainty that are published each month in the eight leading US newspapers (Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal).

Figure 1 plots the evolution of the CPU index (blue line) from January 2000 till April 2023, as well as the average during the previous six months (orange line). As Figure 1 shows, media spread on climate news increased over time, especially in the last years. This way, and given the evolution of the six-monthly CPU average, the extent to which the main US newspapers addressed climate issues overall remained at similar levels from 2000 to August 2013, but experienced a noteworthy increase from then on.

(Insert Figure 1)

3. Empirical analyses

3.1. Persistence in Carbon Risk Score (CRS)

We first analyse persistence in the CRS of US domestic funds on a quarterly basis. Ensuring a high level of persistence is essential to proxy for the funds' level of carbon risk when this information is not available (fund score data are only available from 2017). To do this, we employ a non-parametric approach based on double-entry tables to associate the level of CRS achieved by a fund during two consecutive quarters. That is, each period we sort funds according to their CRS and split the sample into quintiles. Thus, funds included in the top quintile (Q5, or *High*) relate to the highest CRS in the sample, while the bottom quintile (Q1, or *Low*) includes the lowest CRS funds in the sample. We then link the relative levels that each fund experiences during two consecutive quarters to assess score persistence. Accordingly, if there is evidence on persistence in the fund level of CRS, a percentage significantly greater than 20% of the sample will remain in the same quintile during two consecutive quarters.

Table 2 shows the number of observations gathered into the different quintiles in consecutive quarters. Specifically, the table reports the distribution of the 24,408 fund observations covering the last twenty-six quarters of the sample period. Funds with a score in a quarter that do not report any value on the following quarter (e.g., terminated funds, or funds with missing data) are considered as *Disappeared*.

Table 2 evidences a notably high degree of persistence among fund CRS. For instance, 91.39% of the funds (4,467 out of 4,888) remain in the Low quintile during two consecutive quarters. Regarding the top quintile, funds with the highest exposures to carbon risk in a quarter are very likely to obtain a similar relative level in the following quarter (i.e., 86.59% of the fund-quarterly observations repeat in the High quintile during two consecutive periods). Along these lines, almost none of the analysed observations experience any reversal in the corresponding score level (from Low to High, or vice versa). Mid-quintiles also report evidence on high persistency degrees, with percentages no lower than 75%.

(Insert Table 2)

In addition to the above-mentioned analysis, we next examine potential fund differences in the magnitude of the CRS over time. To this aim, each quarter we calculate the cross-sectional average scores for funds included in the same quintile. Figure 2 plots the time-series evolution of the mean score in each quintile. As reported, score averages stay very similar over time, and there is a considerable difference in the mean scores between funds in the High and the Low quintiles (averages of 16.41 and 3.53, respectively).

In other words, results on Table 2 and Figure 2 show that funds, on aggregate, obtain similar CRS over time. More importantly, the degree of carbon risk strongly persists at the individual level. This evidence allows us to proxy for the fund score in periods when this information is missing (before 2017), what is essential to differ among existing funds with higher or lower exposures to companies involved in carbon-based activities. Especially, at earlier periods denoted with a scarce media visibility for climate uncertainty.

(Insert Figure 2)

3.2. Evolution of fund assets and carbon risk levels

The main purpose of this study is to analyse fund investor behaviour in relation to the spread of climate-based articles written in the main US newspapers. Assuming that fund investors can be influenced by the information on the media, larger amounts of news related to climate risk and uncertainty will affect their investment decisions and, consequently, the size of the funds they invest in. So, we start checking this influence in examining the total net assets managed by funds with different exposures to carbon risk.

Although the information on CRS is available from 2017 onwards, the evidence on score persistence shown in the previous section allows us to employ the first available score to proxy for the funds' level of carbon risk in each period before that year. Funds are then sorted into quintiles, based on their level of proxied CRS. As in the previous section, funds categorized as *Low* relate to the 20% of the funds with the lowest levels of CRS in the sample, while *High* refer to funds in the top quintile.

Figure 3 plots the evolution of the aggregate billion dollars managed by funds with similar levels of CRS. Some conclusions are drawn from Figure 3. On the one hand, we should realize that funds, on aggregate, increased the value of their managed assets from 1.4 trillion dollars at the beginning of 1999 to 4.2 trillion dollars as of June 2023. This increasing trend is present among all the quintiles considered. On the other hand, and despite the increase in fund assets across quintiles, the importance of *Low* and *High* carbon risk funds drastically changed in the last years, in favour of the former. And, interestingly, this difference seems to be more noticeable when climate risk issues appear in the main newspapers to a greater extent (mid-2013 on).

(Insert Figure 3)

To observe if funds with different scores are affected by the extent that climate uncertainty is addressed in newspapers, we estimate the following regression:

$$TNA_{q,m} = \beta_0 + \beta_1 CPU_{q,m} + \beta_2 Time\ Trend_m + \varepsilon_{q,m} \quad (1)$$

Where $TNA_{q,m}$ is the monthly aggregated TNA in each quintile q in month m, $CPU_{q,m}$ is the average level of the CPU index in the last six months in month m, and Time $Trend_{q,m}$

is a variable indicating the monthly period of month *m* to capture the increase in overall assets over time.

Results of this analysis are reported in Table 3. Specifically, we report the coefficient estimates and their statistical significance (*t*-stat), as well as the adjusted coefficient of determination.

In line with Figure 3, the last column of Table 3 shows that funds increased the value of their total assets over the sample period. This effect is captured by the positive and statistically significant estimate of the Time trend variable. In case of examining quintiles of CRS, the same positive trend arises.

In relation to the effect of the climate risk related news on the size of the funds, CPU has a non-significant impact on the assets managed by all the funds. Nonetheless, the differences in the effect of CPU across funds with different levels of CRS is noteworthy. Regarding the *High* quintile, an increase in the climate risk articles covered by the main newspapers during the last six months correlates negatively with the total assets managed by funds with the highest carbon risk scores (coefficient of -1.564, t-stat of -6.513). Conversely, *Low* fund assets are affected on a positive and a statistically significant way by the CPU evolution (coefficient of 1.941, t-stat of 3.237).

The evidence in Table 3 involves that an increase in the media visibility about climate risk issues during the previous months entails an increase in the assets managed by *Low*-carbon risk funds, and a decrease in the size of funds with higher carbon risk exposures. As commented above, one potential explanation relates to investor decisions, since their investments and divestments directly affect fund assets. In the following sections, we delve into the effect that the climate risk visibility in the media had on investors decisions over the last twenty-four years.

(Insert Table 3)

3.3. Investor flows to funds with different scores

In the previous Section, we observed that funds with lower carbon risk exposures increased their importance, in terms of assets under management. This increase was significantly affected by the media visibility about climate uncertainty news, which was more relevant during the last years. In this Section, we examine whether fund investor decisions are affected by the extent to which climate risk is addressed in the main newspapers.

Firstly, we proxy for fund investors decisions at the fund level using methodology shown in Sirri and Tufano (1998). That is, each month we estimate net cash flows of fund investors in comparing the monthly assets managed by a fund with the asset value that the fund would have managed in case of no experiencing any investor flows during the previous period. Net cash flows are expressed on a percentage basis, in relation to the assets held in the fund portfolio in the previous period.

Since the magnitude of net flows rely on the scale of the fund, we first sort funds into quintiles, according to the total net assets managed in the previous month. Five subsamples comprising funds with similar levels of TNA (from smaller to larger funds) are considered each period. We then split each subsample into quintiles, based on the assumed carbon risk score in the previous month (from *Low* to *High* scores). This sorting process generates 25 subsamples in relation to the levels of fund size and scores.

Next, and for each month, we calculate the average net flows of fund investors in each subsample. To observe any differences in the overall investor behaviour in relation to the fund level of carbon risk (while controlling simultaneously for fund scale), we estimate the mean differences (and significance) between the average flows of *High* and *Low*-score funds in each size subsample.

The analysis is applied to the whole sample period as well as for two sub-periods related to the evolution of media visibility about climate risk and uncertainty issues to assess whether the relation between fund scores and investor flows changed over time. Results of this analysis are reported in Table 4.

(Insert Table 4)

Regarding the whole sample period, we do not observe any significant differences in the average of investor flows between funds with the highest and the lowest carbon risk exposures. Nonetheless, we should note that the whole sample period encompasses two different trends in the extent to which climate issues are addressed in the main US newspapers.

As Figure 1 showed, the first sub-period does not relate to any important variations in the number of articles focusing on climate issues. During that period, funds with the highest exposures to carbon risk attracted, on aggregate, higher levels of investor flows than *Low*-carbon funds (difference in the average of monthly flows: 0.22%; t-stat: 1.755). This is, however, an average effect driven by some funds in the sample. We observe that this positive difference in favour of High-score funds is only significant among the *Large* quintile (i.e, among those funds managing the highest amounts of money).

Conversely, the last sub-period is characterized by an upward trend in the CPU index, entailing a relevant increase in the media visibility of climate risk and uncertainty. As Table 4 shows, this increase in the media visibility affects fund investor flows. In contrast to the first sub-period, High-score funds experienced significantly lower net cash flows than funds with the lowest levels of carbon risk. In the aggregate, the average flow difference is -0.15% per month, with an associated t-statistic of -2.115. This evidence remains in most of the fund size groups considered. For instance, the average High-Low difference among funds managing the highest asset values is -0.19% per month (t-stat: -3.193), and a monthly -0.27% among the smallest funds in the sample (t-stat: -2.602).

In sum, results in Table 4 shows that investors changed their fund ~~score~~ preferences in the last years. Accordingly, funds reporting the previous highest carbon risk scores experienced lower investor flows, on a net basis, than funds associated with lower carbon risks. Given the evidence in Table 3 and Table 4, we attribute this change to the striking media spread of climate risk and uncertainty news.

3.4. Changes in the flow-performance relationship

We next examine the relationship between investor flows and previous fund performance among funds with similar levels of carbon risk. To observe any variations in investor decisions in relation to the increase in climate visibility in the media, we focus on the aggregate flows to High and to Low score funds in both subperiods.

Specifically, funds with similar scores are sorted according to their financial performance in the previous twelve months. Financial performance is measured in two different ways: as the average net return, and as the alpha derived from a market-factor model. To ensure the consistency of the results, funds are required to present complete data on monthly returns during the previous year to be considered in the analysis.

Based on their financial performance, funds are grouped into quintiles, from *Worst* to *Best*-performing funds. This sorting process is repeated each month from January 2000 to the end of the sample period. To illustrate the flow-performance relationship among funds with the highest (*High*) and the lowest (*Low*) carbon risk scores, we plot on Figure 4 the average of net flows (in percentage over the previous fund assets) for each performance-based quintile. Flow results in relation to fund net returns are reported in Figure 4a, while those related to fund alphas are reported in Figure 4b. To delve into any changes in fund investor behaviour in relation to the dissemination of climate news spread in the media, Table 5 additionally shows the average differences in investor flows to *High* and *Low*-score funds with similar relative levels of previous performance in both subperiods. Results for average flow differences related to fund net returns and alphas are reported in Panel A and Panel B, respectively.

(Insert Figure 4)

Figure 4 shows very interesting results. On the one hand, and in line with the previous literature (see, e.g., Ivković and Weisbenner, 2009; Ferreira *et al*., 2012; Wang *et al*., 2018), investor flows are positively related to previous fund performance. This is reflected on the positive slope evidenced across previous performance quintiles. This implies that funds achieving the highest performance levels do experience subsequent positive net cash flows, while a poor fund performance involves negative investor net flows in the future. This overall evidence remains for both High and Low carbon risk funds and for both sub-periods.

On the other hand, we observe that investor decisions to *High* and to *Low* carbon risk funds did in fact change in the last years. Regardless of the positive relationship between previous performance and future net flows among both type of funds, the left-side Figures show that funds with the highest carbon exposure experienced, on aggregate, subsequent higher average investor flows than *Low*-carbon risk funds. As Table 5 shows, this evidence is statistically significant in most of the performance-based quintiles examined. For instance, and regarding fund net returns (results in Panel A), the High-Low difference in fund flows ranges from +0.27% (t-stat: 2.127) for the worst-performing funds to +0.48% per month (t-stat: 2.075).

Nevertheless, and as the media intensified their attention to climate risk and uncertainty news, *High*-score funds experienced lower investor flows than funds with lower carbon risk levels that performed similarly. As shown in Figure 4, and in contrast to the evidence in the first sub-period, average flows to *High* funds (orange line) fall below those in *Low* carbon risk funds (blue line) in the second sub-period. Results in Table 5 shows that the average flow difference is negative and statistically significant for most levels of the fund performance (e.g., the High-Low difference among the best performing funds is -0.28% per month for both fund returns and alphas). Results on the worst-performing funds are the only exception, but the High-Low positive difference in monthly flows (ranging from 0.13% to 0.15%) is not statistically significant.

(Insert Table 5)

In sum, results in Figure 4 and Table 5 show that investors go into funds exhibiting higher past performance to a greater extent. Accordingly, the flow-performance relationship is shown to remain positive over time. Nonetheless, previous financial performance is not the only factor affecting fund investors. As documented, and in line with the evidence reported in the previous sections, media spread of climate risk news also influences their investment decisions. This way, net cash flows experienced by funds with higher carbon risk exposures are significantly lower than flows into similar-performing *Low*-carbon risk funds in a period associated to a noteworthy increase in the CPU index.

3.5 Determinants of fund investor flows

Next, we aim to assess the effect of the media dissemination of climate risk and uncertainty news on future investor flows to funds with different carbon risk exposures. To examine this relationship at the fund individual level, we employ panel regressions to control for fund determinants that could affect investor flows.

We implement four models to explain investment flows. The main explanatory variables refer to the average CPU index during the previous six months, and two interaction variables to capture for different fund sensitivities to climate news. Specifically, each interaction variable is computed as the product of the six-monthly average CPU index with a dummy variable indicating that the fund is comprised among those with the highest (*High*) or the lowest (*Low*) carbon risk scores.

Other fund characteristics that explain fund flows are also included in the analyses. In regards of the analyses shown in the previous sections, Model 1 and Model 2 also control for previous fund size and financial performance. Previous size is measured as the logarithm of total net assets at the beginning of each month. Previous performance is estimated using the previous monthly return (Model 1) and the previous alpha derived from a market-factor model (Model 2). Both models include a variable indicating the monthly period to capture for any time trend on fund net cash flows.

Additionally, Model 3 and Model 4 extend these models in including other fund characteristics potentially affecting fund flows. These include the previous fund age (log of the months since fund inception), and fund costs (annual net expense ratio) and portfolio turnover (log of turnover ratio). Furthermore, we control for any autocorrelation in the percentage of fund net flows in including the dependent variable lagged one period. Regression results are shown in Table 6.

(Insert Table 6)

Regarding Model 1 and Model 2, Table 6 shows that fund size is negatively related to investor net cash flows. This result is not surprising since the higher the fund scale is, the lower the average flows are as a percentage of total net assets. In relation to fund performance, the conclusions extracted are in line with Figure 4. That is, higher fund performance attracts higher levels of future net cash flows. The effect of the CPU index on the flows of the mid-score carbon risk funds (from Q2 to Q4) is not clear and depends on the model considered. Nonetheless, *Low*-carbon risk funds show a significantly greater sensitivity to the evolution of the number of climate news than the rest of the sample. Specifically, the coefficient on the interaction variable between the CPU index and the *Low* dummy is positive and statistically significant (in Model 1, coefficient: 0.0012, t-stat: 2.39). In contrast, the interaction representing the additional sensitivity of *High*-score fund flows to the CPU behaviour is negative but not statistically significant.

In considering other flow determinants to explain fund flow variability (Model 3 and Model 4), we find similar evidence for size, financial performance and climate risk news. In addition, results show that fund age, an explanatory variable that is likely to be related with fund size, also correlates negatively to net flows. In contrast, the percentage of fund flows persists over time, given that the coefficient on lagged variable is positive and statistically significant (regarding Model 3, coefficient: 0.3519; t-stat: 33.65). Other factors, such as fund expenses and portfolio turnover, have a non-significant effect on investor net cash flows.

Along these lines, we should realize that the aforementioned results rely on aggregate investor flows, expressed on a net basis, and without differentiating between their investment and divestment decisions. In the following analyses, we test whether the effect of the media visibility on climate risk and uncertainty specifically affect fund inflows (new investors' money going into the fund) and outflows (fund redemptions due to investors' exit decisions).

To this aim, we retrieve data for fund monthly inflows and outflows from Morningstar. Data are available since mid-1999 for most of the funds in the sample. These variables, however, suffer from missing data, and most of the existing funds do not present any information on inflows and outflows during 2018 and 2019. Despite this issue, we first re-apply Model 3 and Model 4 in considering inflows and outflows as dependent variables. Both flow measures are expressed as a percentage of fund assets. Table 7 reports the main results of this analyses.

Most of the evidence in Table 7 is in line with previous results. On the one hand, and since fund inflows positively affect net cash flows, we should expect similar effects of the explanatory factors on investor inflows as those reported in Table 6. Indeed, Table 7 shows similar coefficients for the considered control variables. For instance, previous financial performance and previous fund inflows present significantly positive estimates, while lags of fund size and age have a negative effect.

Also, investor redemptions impact negatively on fund net cash flows. As we could expect, higher returns diminish the percentage of investor outflows that a fund experiences in subsequent periods. Consequently, estimates for fund returns and fund alphas are both negative (-0.0218 and -0.0756, respectively) and statistically significant (t-stats of -15.16 and -4.57). Previous fund size, previous portfolio turnover and lagged outflows present positive and statistically significant coefficients on fund outflows.

On the other hand, and regarding the effect of the CPU index, Table 7 shows that it correlates positively to fund inflows and outflows. This explains the non-defined effect on net cash flows shown in Table 6. Regarding the interaction variables, we do not observe that *High* and *Low*-score fund inflows behave differently to an increase in climate news than mid-score funds. Nevertheless, the coefficient for the interaction *Low*-fund variable is negative (-0.0015 in Model 4) and statistically significant (t-stat: -3.08).

In sum, the evidence in Table 7 delves into the relationship between investor behaviour to funds with different carbon risk exposures and the extent to which climate news are spread in the newspapers. Previous results showed that Low-carbon risk funds experience higher net cash flows when the CPU index increases. That evidence is mainly driven by investor outflows, entailing that a higher amount of climate and uncertainty news generate lower redemptions among *Low*-carbon risk funds.

Finally, we test for any changes in investor behaviour to High and Low-carbon risk funds due to the noteworthy increase in the media visibility on climate issues. Similar to previous analyses, we split the sample period into two sub-periods related to the trend of the CPU index. We then repeat analogous panel regression analyses as those in Table 6 and Table 7, and report the main results in Table 8. Panel A and Panel B report the results for the first and the second sub-periods, respectively. For the sake of brevity, we only report the results derived from Model 4 for the six-monthly CPU index and for the potential sensitivities in the flows of *High* and *Low*-score funds.

(Insert Table 8)

As Table 8 shows, the CPU index has a significantly positive effect on fund inflows (in the first sub-period) and outflows (in both sub-periods). The behaviour of fund investors changed as climate news increased their relevance in the newspapers. Accordingly, and regarding the first sub-period, flows going into and out of *Low*-carbon funds did not experience any significantly different response to an increase in the CPU index than other funds in the sample, while *High*-score funds received lower amounts of new money from investors. Regarding the second sub-period, the increase in the media attention on climate issues affected investor decisions, generating lower redemptions among funds with the lowest carbon risk exposures, and consequently involving higher flows on a net basis.

4. Conclusions

This study aims to assess the impact that media visibility on climate news has on fund investor behavior. Media visibility is proxied by the evolution of the number of articles addressing climate issues published in the US leading newspapers. To fulfil this objective, we analyse a sample of 1,352 US domestic equity funds during the period 1999-June 2023, and examine the investors' flow-carbon risk relationship over time.

Our results show that climate news affect the behaviour of fund investors, indeed. On the one hand, funds bearing lower carbon risk increased their importance in more recent periods, in contrast to funds linked to higher carbon exposures. This increase is partially explained by the wider media dissemination made in the last years. Moreover, funds with the highest carbon risk exposures experienced lower investor flows than low-carbon funds from 2013 on, regardless of the previous fund scale and financial performance achieved.

This paper contributes to the extant literature explaining the factors that contribute to mutual fund investor decisions. Specifically, this study examines the fund investors response to climate-related risks associated with the transition to a low carbon economy. Moreover, the study also contributes to the literature that examines the influence of public attention to environmental issues on investment decisions.

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Figure 1. Evolution of the CPU during the 2000/00-2023/04 period

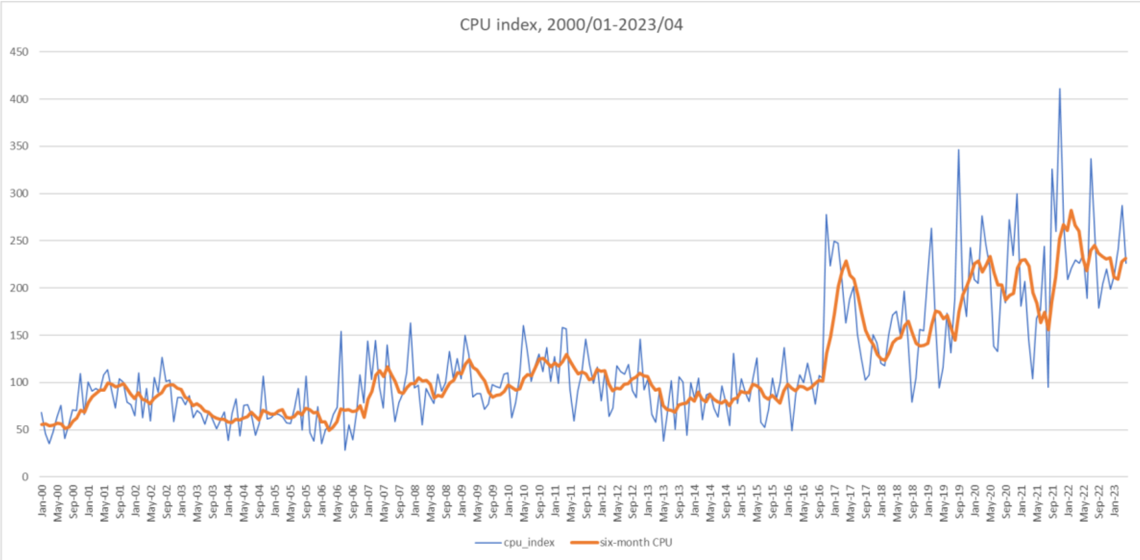

Figure 2. Mean carbon risk scores on fund quintiles

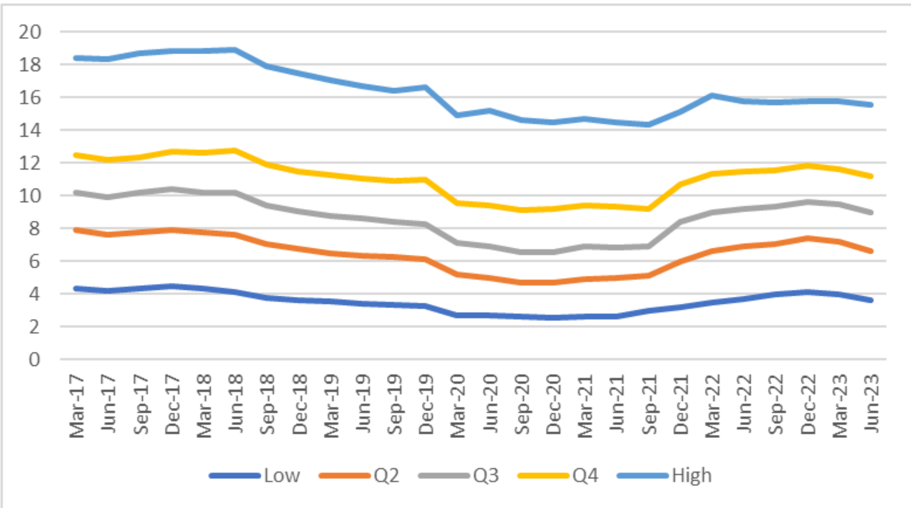

Figure 3. Aggregate TNA on fund quintiles based on CRS

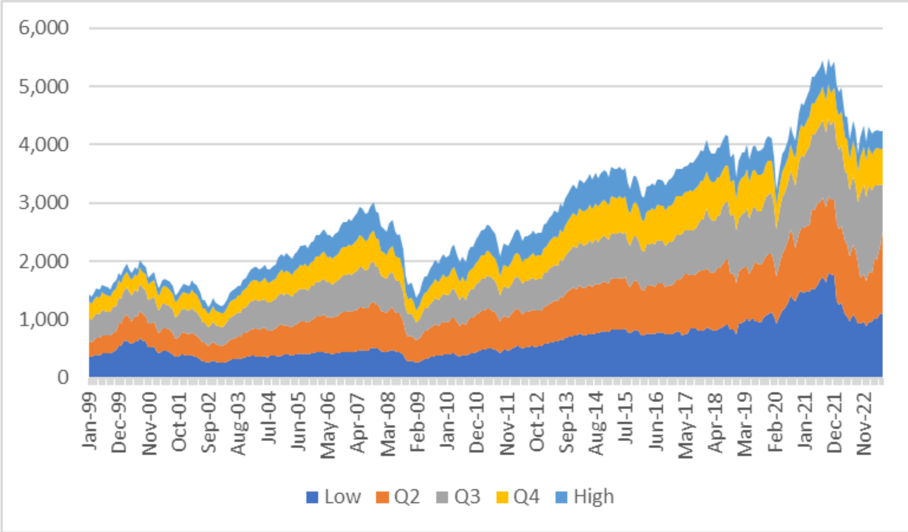

Figure 4. Flow-performance relationship among High and Low-carbon risk funds

Figure 4.a. Flow-performance relationship. Sorting on previous 12-month average return

Subperiod 1: 2000/01-2013/07 | Subperiod 2: 2013/08-2023/06

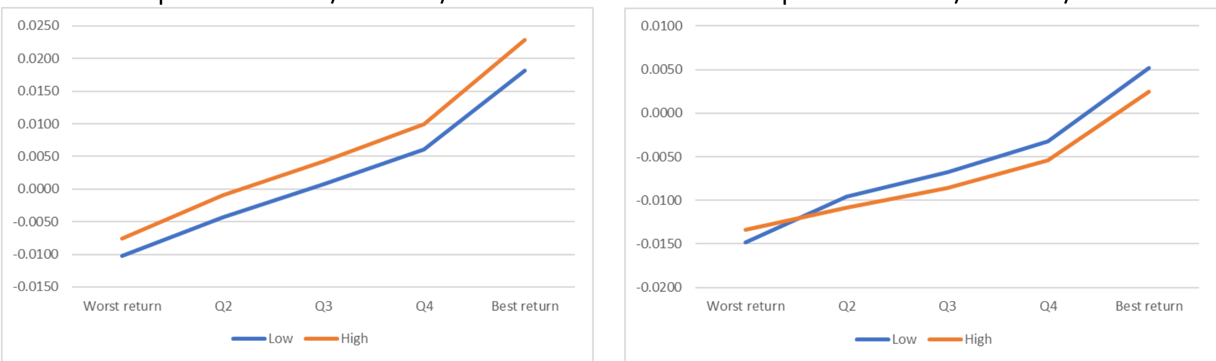

Figure 4.b. Flow-performance relationship. Sorting on previous 12-month average alpha

Subperiod 1: 2000/01-2013/07 | Subperiod 2: 2013/08-2023/06

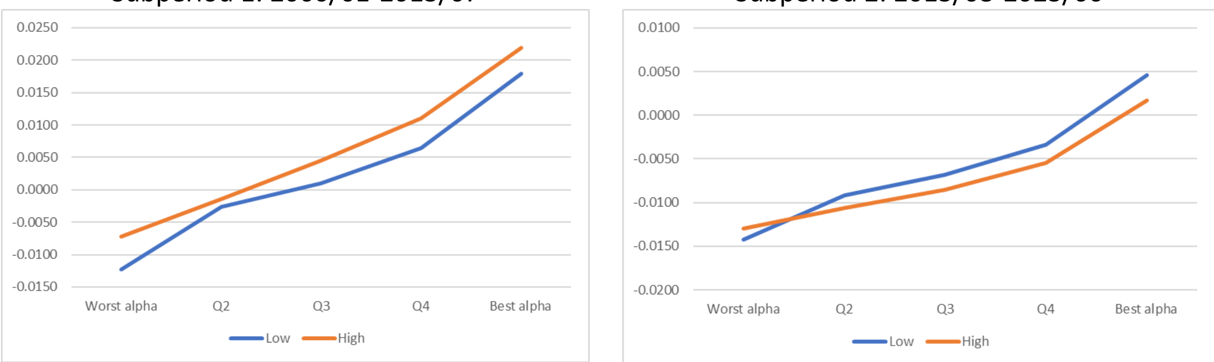

Table 1. Descriptive statistics of the sample

	Average	Median	s.d.
Carbon Risk Score	9.6169	9.3476	5.0057
Net Return (%, annualized)	8.6861	15.2992	1.6393
Total Net Assets (in USD million)	1,419.43	305.08	5,194.38
Net Cash Flows (%)	-0.0404	-0.1106	0.6996
Fund age (months)	187.67	148.01	168.90
Turnover ratio (%)	93.8026	71.5000	110.1877
Net Expense Ratio (%)	1.3761	1.3312	0.7958

This Table shows the main descriptive statistics for the sample of funds during the period January 2000-June 2023. Specifically, the average, median and standard deviation are computed for each variable. Net returns are annualized from a monthly basis. Net Cash Flows are computed as in Sirri and Tufano (1998), and are expressed as a percentage of fund assets. Fund age refers to the number of months since fund inception. All the variables are winsorized at 0.5% in each tail to avoid extreme outliers.

Table 2. Persistence in the fund level of carbon risk

		Quarter *t*						
		Low	Q2	Q3	Q4	High	Disappeared	All obs.
Quarter *t-1*	Low	4,467	323	6	0	0	92	4,888
	Q2	377	3,921	503	7	1	82	4,891
	Q3	3	584	3,737	448	5	92	4,869
	Q4	1	15	514	3,775	457	115	4,877
	High	1	2	14	523	4,228	115	4,883
	All obs.	4,849	4,845	4,774	4,753	4,691	496	24,408

Table 3. Explaining the funds' aggregate TNA on CPU index

	Aggregate TNA managed by funds on quintiles based on Carbon Risk Score.					
	Low	Q2	Q3	Q4	High	All funds
Constant	111.835*	256.216***	191.383***	283.069***	247.485***	1,089.987***
t-stat	1.824	7.512	4.971	15.247	12.447	8.847
Six-monthly CPU	1.941***	0.344	1.736***	-0.831***	-1.564***	1.626
t-stat	3.237	0.872	3.958	-3.295	-6.513	1.217
Time trend	2.137***	2.738***	1.952***	1.764***	1.881***	10.472***
t-stat	5.519	13.613	8.789	13.585	13.509	12.812
Adj. R^2	0.6853	0.8308	0.7860	0.7104	0.6952	0.8394

The dependent variable is the aggregate size (in billion dollars) for funds in each quintile, sorted on previous carbon risk scores. T-stats are from Newey-West standard errors.

Table 4. Flow differences in funds with High and Low carbon risk exposures

	Whole period 1999/01-2023/06		Subperiod 1 1999/01-2013/07		Subperiod 2 2013/08-2023/06	
High-Low Carbon Risk	Average Flow difference	t-stat	Average Flow difference	t-stat	Average Flow difference	t-stat
Size Q1 (Small)	0.0004	0.222	0.0025	1.084	-0.0027***	-2.602
Size Q2	0.0007	0.540	0.0008	0.452	0.0005	0.538
Size Q3	-0.0002	-0.197	0.0001	0.042	-0.0006	-0.660
Size Q4	-0.0007	-0.730	0.0005	0.438	-0.0024***	-2.874
Size Q5 (Large)	0.0004	0.588	0.0020**	1.981	-0.0019***	-3.193
All funds	0.0007	0.734	0.0022*	1.755	-0.0015**	-2.115

Funds are sorted into quintiles according to their previous TNA (first) and score (then). Each coefficient reflects the difference in the net flow average between the High-score and the Low-score funds. T-stats are for mean differences between both time-series. Statistically significant mean differences are denoted with asterisks ('*', '**', and '***', for 10%, 5%, and 1% of significance, respectively).

Table 5. Flow differences in funds with High and Low-carbon risk exposures with similar performance

Panel A: High-Low score investor flows	Subperiod 1: 2000/01-2013/07		Subperiod 2: 2013/08-2023/06	
	Average Flow Difference	t-stat	Average Flow Difference	t-stat
Return Q1 (Worst)	0.0027**	2.127	0.0015	1.390
Return Q2	0.0034***	2.877	-0.0013*	-1.836
Return Q3	0.0035***	2.950	-0.0018***	-2.431
Return Q4	0.0039***	2.655	-0.0022***	-2.854
Return Q5 (Best)	0.0048**	2.075	-0.0028**	-2.121

Panel B: High-Low score investor flows	Subperiod 1: 2000/01-2013/07		Subperiod 2: 2013/07-2023/06	
	Average Flow Difference	t-stat	Average Flow Difference	t-stat
Alpha Q1 (Worst)	0.0051***	3.927	0.0013	1.219
Alpha Q2	0.0013	1.100	-0.0014*	-1.891
Alpha Q3	0.0035**	2.936	-0.0017**	-2.362
Alpha Q4	0.0046***	3.053	-0.0020***	-2.528
Alpha Q5 (Best)	0.0040*	1.780	-0.0028**	-2.232

Funds are sorted into quintiles according to their financial performance in the previous twelve months. Financial performance is measured as the average net return (Panel A) and the alpha derived from a market-factor model (Panel B). Each coefficient reflects the difference in the net flow average between the High-score and the Low-score funds. T-stats are for mean differences between both time-series. Statistically significant mean differences are denoted with asterisks ('*', '**', and '***', for 10%, 5%, and 1% of significance, respectively).

Table 6. Explaining fund net flows on the CPU and other fund characteristics

	Model 1		Model 2		Model 3		Model 4	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
sixmonthCPU	0.0013***	3.05	-0.0009**	-2.14	-0.0003	-0.92	-0.0012***	-4.51
sixmonthCPU*Low	0.0012**	2.39	0.0011**	2.34	0.0009***	2.82	0.0006**	2.14
sixmonthCPU*High	-0.0005	-1.11	-0.0002	-0.51	-0.0004	-1.52	-0.0001	-0.48
LagSize	-0.3178***	-12.41	-0.2265***	-9.44	-0.0018***	-11.60	-0.0019***	-11.69
LagReturn	6.5536***	26.62			0.0366***	21.26		
LagAlpha			89.9062***	32.98			0.5502***	31.06
LagAge					-0.0105***	-13.64	-0.0095***	-12.64
LagExpenses					-0.0487	-0.66	-0.0787	-1.06
LagTurnover					0.0001	0.49	-0.0001	-0.52
LagFlows					0.3519***	33.65	0.3338***	33.13
Constant	-0.0081***	-21.19	-0.0044***	-12.32	0.0887***	16.93	0.0859***	16.28
R-square	0.0390		0.0638		0.1596		0.1739	
Time trend	Yes		Yes		Yes		Yes	
Fixed-effects	Yes		Yes		Yes		Yes	

Dependent variable is fund net cash flows, in percentage over the previous fund TNA. Explanatory variables include the previous lags for fund size (log of TNA), financial performance (monthly return and alpha), fund age (log of months since inception), and the last available net expense ratio and portfolio turnover (log of turnover ratio). Previous fund flows are also considered, as well as a variable capturing the time trend. Fund fixed effects are applied according to the Hausman test. T-stats are from HAC standard errors clustered by fund. Statistically significant coefficients are denoted with asterisks ('**', and '***', for 5%, and 1% of significance, respectively).

Table 7. The determinants of fund inflows and outflows

	Inflows				Outflows			
	Model 3		Model 4		Model 3		Model 4	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
sixmonthCPU	0.0024***	7.12	0.0019***	5.65	0.0036***	11.83	0.0039***	13.06
sixmonthCPU*Low	-0.0004	-0.79	-0.0006	-1.24	-0.0014***	-3.02	-0.0015***	-3.08
sixmonthCPU*High	-0.0003	-0.88	-0.0001	-0.41	-0.0001	-0.35	-0.0001	-0.22
LagSize	-0.0013***	-5.19	-0.0014***	-5.50	0.0013***	5.51	0.0013***	5.61
LagReturn	0.0102***	4.80			-0.0218***	-15.16		
LagAlpha			0.3713***	18.60			-0.0756***	-4.57
LagAge	-0.0084***	-8.25	-0.0076***	-7.64	<-0.0001	<-0.01	-0.0002	-0.19
LagExpenses	-0.1023	-1.08	-0.1852**	-2.02	-0.0344	-0.37	-0.0843	-0.94
LagTurnover	0.0010***	3.63	0.0008***	2.84	0.0015***	5.50	0.0014***	5.42
LagFlows	0.4738***	36.59	0.4624***	34.50	0.3671***	17.30	0.3671***	16.94
Constant	0.0839***	12.22	0.0836***	12.25	-0.0092	-1.56	-0.0076	-1.29
R-square	0.2738		0.2799		0.1566		0.1547	
Time trend	Yes		Yes		Yes			
Fixed-effects	Yes		Yes		Yes			

Dependent variables are fund inflows and outflows, in percentage over the previous fund TNA. Explanatory variables include the previous lags for fund size (log of TNA), financial performance (monthly return and alpha), fund age (log of months since inception), and the last available net expense ratio and portfolio turnover (log of turnover ratio). Previous fund flows are also considered, as well as a variable capturing the time trend. Fund fixed effects are applied according to the Hausman test. T-stats are from HAC standard errors clustered by fund. Statistically significant coefficients are denoted with asterisks (‘**’, and ‘***’, for 5%, and 1% of significance, respectively).

Table 8. Addressing sub-periods with different trends of climate risk and uncertainty news

Panel A. Sub-period 1: 1999/01-2013/07	NetCashFlows		Inflows		Outflows	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
sixmonthCPU	-0.0073***	-7.28	0.0003	0.27	0.0075***	10.49
sixmonthCPU*Low	0.0021	1.19	0.0010	0.58	-0.0021	-1.48
sixmonthCPU*High	-0.0038*	-1.77	-0.0062**	-2.56	-0.0022	-1.08
Control variables?	Yes		Yes		Yes	
Time trend?	Yes		Yes		Yes	
Fixed Effects?	Yes		Yes		Yes	

Panel B. Sub-period 2: 2013/08-2023/06	NetCashFlows		Inflows		Outflows	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
sixmonthCPU	0.0003	1.17	0.0039***	9.94	0.0049***	11.81
sixmonthCPU*Low	0.0007**	2.21	-0.0006	-1.06	-0.0014***	-2.88
sixmonthCPU*High	-0.0004	-1.40	0.0001	0.15	0.0003	0.83
Control variables?	Yes		Yes		Yes	
Time trend?	Yes		Yes		Yes	
Fixed Effects?	Yes		Yes		Yes	

Dependent variables are fund flows, in percentage over the previous fund TNA. Explanatory variables are those described in Model 4 of Table 6 and Table 7. Fund fixed effects are applied according to the Hausman test. T-stats are from HAC standard errors clustered by fund. Statistically significant coefficients are denoted with asterisks ('**', and '***', for 5%, and 1% of significance, respectively).