How Different Are ESG Mutual Funds? Evidence and Implications

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March 2, 2022

Abstract

Investment funds marketed as "sustainable" or "ESG" (Environmental, Social and Governance) have proliferated in recent years. In the wake of this trend, skepticism is looming among the public over the trustworthiness of these financial actors and the distinctiveness of their investment practices compared to those of regular actors. Using a panel data set of 2,042 U.S. equity mutual funds, we empirically examine whether such funds actually differ from their conventional peers in terms of investment strategies, the returns they offer to their investors, and the capital flows they attract from the latter over the period 2013q1–2018q4. We further show how it evolves over time, and in response to climate concerns. Regarding investment strategies, our findings indicate that the portfolio compositions of high-ESG funds differ from those of their conventional peers and, more surprisingly, from each other. As time goes by, high-ESG and conventional groups become increasingly similar, while high-ESG portfolios become more homogeneous. In terms of financial performance, our results suggest that, on average, high-ESG funds underperform their conventional peers. However, they show greater resilience to climate risk, erasing the gap in financial performance between the two groups when climate risk surges. Finally, our findings provide evidence that climate risk increases capital flows, especially into less distinctive mutual funds. Nevertheless, we cannot find any difference in capital flows between high-ESGs and conventional funds.

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"Last year we wrote to you that BlackRock was making sustainability our new standard for investing. We outlined how we were making sustainability integral to the way we manage risk, generate alpha, build portfolios, and pursue investment stewardship, in order to help improve your investment outcomes. We made this commitment on the strength of a deeply-held investment conviction: that integrating sustainability can help investors build more resilient portfolios and achieve better long-term, risk-adjusted returns. In 2020, we completed our goal of having 100% of our active and advisory portfolios ESG-integrated. [...] climate risk is investment risk, which would drive a significant reallocation of capital." (BlackRock's Global Executive Committee, 2021)[1]

"Investor scepticism on ESG points to a maturing market. Concerns about greenwashing have grown as sustainable finance has gone mainstream." (Financial Times, 2021)[2]

1 Introduction

Concerns about climate change have increased dramatically over the past decade. At remarkable demonstrations, young citizens worldwide have called for an acceleration of the transition toward a low-carbon economy, pushing this issue to the top of the policy agenda. Changes in market regulation and tax regimes have been phased in to encourage climate-friendly investment and achieve ambitious goals in this area. Nowadays, it is widely acknowledged that the financial industry plays a pivotal role in this process by channeling capital into sectors and firms conducting sustainable activities (e.g., NGFS, 2019). In 2015, the Paris Agreement explicitly named "making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development" as an objective (United Nations, 2015). In a large survey of financial investors, Krueger et al. (2020) provide illuminating evidence on how deeply such considerations about climate change and sustainable development have penetrated into the financial sector and are now influencing a wide range of day-to-day decisions.[3]

Currently, the vast majority of institutional investors expect global temperatures to rise markedly by the end of the century, with likely dramatic effects on financial assets. These concerns are leading them to adapt their practices, be it to protect their reputation, or

[1] See the BlackRock's 2021 letter to clients by the BlackRock's Global Executive Committee (2021/01/26).

[2] See the article "Investor scepticism on ESG points to a maturing market" by the Financial Times (2021/10/17)

[3] This survey was conducted among 439 institutional investors. In the same vein, a survey of 1,000 individual investors by Morgan Stanley (2017) highlighted that 75% were interested in sustainable investing.

comply with ethical considerations or legal duties. In practice, it generally translates into the adoption of Environmental, Social, and Governance (ESG) criteria in their investment process, as illustrated by the opening quote from the annual letters of BlackRock' Global Executive Committee to their clients (see also Krueger et al., 2020 for more general evidence). As is well-documented in the literature, ESG ratings and labels have emerged in recent years as a critical tool to guide investor decisions, with high-ESG score products, firms or funds viewed as those complying the most substantially with sustainability constraints (Coqueret, 2021).

The sudden "hype" surrounding sustainable finance and the associated transformation of the industry, however, is not without raising important concerns. In particular, given the lack of a consistent and clear definition, combined with the proliferation of investment vehicles marketed as "sustainable," skepticism is looming among the public about how trustworthy these financial actors are, and how distinctive their investment practices actually are compared to those of regular actors (Kim and Yoon, 2020). The notion of "greenwashing"—i.e., "making unsubstantiated or misleading claims about the company's environmental commitment" (Flammer, 2021), which was coined in the 1980s—illustrates this issue all too well; it is now considered one of the main obstacles for investors when it comes to sustainable investing.[4] Given that sustainable investment is going mainstream, the goal of this study is to contribute to the literature by empirically assessing the difference(s) between sustainable and traditional investment approaches in the mutual fund industry over time.

To this end, we investigated whether mutual funds with high ESG ratings (hereafter high-ESG mutual funds, or high-ESGs for short) were different from their conventional peers, and to what extent. We examined three levels: (i) investment strategies as measured by portfolio composition, (ii) financial returns, and (iii) fund flows. Considering the growing importance

[4]See the opinion "Financial world greenwashing the public with deadly distraction in sustainable investing practice" published in USA Today (2021/03/16) by Tariq Fancy and the the online article "Greenwashing tops investors' concerns around ESG products, new research finds" published by Quilter (2021/05/24). Recent contributions that study greenwashing practices in the financial sector include Berrone et al., 2017; El Ghoul and Karoui, 2021; Lyon and Maxwell, 2011; Marquis et al., 2016; it is worth noting that Candelon et al. (2021) extend the notion to all ESG dimensions ("ESG-washing").

of climate change as a source of risk for financial markets (e.g., Litterman et al., 2020), we explore how climate risk impacts the differences between these groups. For instance, we tested the belief (widely shared among market actors) that ESG investing is a way to hedge climate change risk[5] by assessing whether high-ESG funds do indeed perform better than conventional funds when climate risk surges. We also explored whether in periods of heightened climate risk, related to natural disasters for instance, investors might pay more attention to socially responsible considerations and increase investments in mutual funds with a sustainable focus.

As further detailed below, we measured differences between fund investment strategies through portfolio holdings (dis-)similarity. We primarily considered the similarity of mutual fund groups (i.e., holdings of high-ESG funds vs holdings of conventional funds) but we also explored similarity within each group (e.g., holdings of a high-ESG mutual fund vs holdings of other high-ESG funds), that is to say, at the fund level, in order to spot the influence of a distinctive strategy in the spirit of Sun et al. (2012). Overall, the combination of these different features—portfolio holding-based similarity, fund performance and flows, and climate risk—provided useful material to test several hypotheses and to address or, at least, discuss several timely questions about sustainable investment in the mutual fund industry, such as: are portfolio holdings of high-ESG mutual funds actually different from those of conventional mutual funds? If so, is this difference widening, narrowing or remaining stable over time? Is the high-ESG group homogeneous in terms of holdings? Can high-ESG be considered an investment style per se? Do we have to worry about excessive concentration and overlap among high-ESG mutual funds? Are high-ESG funds actually more resilient to climate risk? Can we observe any short-term reallocation of flows toward high-ESG mutual funds as climate risk increases? Are high-ESG mutual funds—the most distinctive among sustainable funds, that is to say, those with the most original investment strategy—associated with a higher financial performance?

[5]In their survey of institutional investors, Krueger et al. (2020) showed that 32% of respondents managed climate risks by incorporating ESG considerations into their investment process.

To tackle these questions, we created a new database including three building blocks. First, we built a metric for pairwise investment strategy similarity ($Pairwise\,Similarity$) based on the Manhattan distance of portfolio holdings of every two funds, updated quarterly.[6] From this pairwise metric, we derived a fund-specific similarity metric ($Similarity$), which we computed as the average of pairwise similarity at the fund level.[7] Second, we collected the Portfolio Sustainability Score, which measures how well a fund's holdings perform on ESG issues, from Morningstar—one of the main sources of information for market participants and scholars alike regarding both sustainable investing and investment funds in general.[8] On the basis of this score, we segmented the universe of U.S. equity mutual funds into sustainable and conventional funds. For the core of our work, we defined high-ESG as the top 10%.[9]

It is worth clarifying at this stage that, by restricting our analysis to the Sustainalytics ESG score provided by Morningstar, our perspective is that of a regular investor willing to select a mutual fund by making use of one of the most influential sources of information in the market (Del Guercio and Tkac, 2008) and wondering to which extend those funds are

[6] While some authors use market-based data to assess peer deviation (e.g., Béreau et al., 2020; Cremers and Petajisto, 2009; Sun et al., 2012; Vozlyublennaia and Wu, 2018), others rely on portfolio holdings data (e.g., Choi et al., 2017; Cremers and Petajisto, 2009; Kacperczyk et al., 2005). Although investment information is much more difficult to obtain and consolidate than market data, it provides a clearer picture of how management decisions impact portfolio similarity.

[7] Portfolio similarity and distinctiveness being two sides of the same coin, we derive pairwise and aggregate distinctiveness metrics, denoted *Pairwise Distinctiveness* and *Distinctiveness*, respectively, from pairwise and aggregate similarity metrics.

[8] Morningstar is considered among the most reliable and critical sources of information in the mutual fund industry (Del Guercio and Tkac, 2008) and asks whether these funds are different from their conventional peers. The existent literature is rife with anecdotes or evidence of how important its information is to professionals. Ben-David et al. (2019), for instance, emphasize the sound recognition of Morningstar's expertise and its reputation as an independent agency, noting that "investors [...] take Morningstar's advice at face value." Over the past two decades, this source has been widely used in academic literature (e.g., Almazan et al., 2004; Brown and Goetzmann, 1997; Del Guercio and Tkac, 2008). In addition to traditional fund information, Morningstar proposes sustainability metrics at the fund level, including the Portfolio Sustainability Score, and constitutes a recognized source of information in the literature on mutual funds' sustainable investment practices (e.g., Ammann et al., 2019; Candelon et al., 2021; Ceccarelli et al., 2021; Hartzmark and Sussman, 2019; Pástor et al., 2020).

[9] We used the 10% threshold for our baseline model for mainly two reasons. First, it corresponds to the percentage of self-declared sustainable funds in our sample. Second, it corresponds to the highest category of the fund-level Morningstar Sustainability (or Globe) Rating: a fund receives five globes and is rated "High" if it is in the top 10% of funds in the category. This top 10% has been used in various studies to flag sustainable funds (see, for instance, Hartzmark and Sussman, 2019, who gave a "high sustainability" label to five-globe funds). Compared to the Portfolio Sustainability Score, the Globe rating's main drawback is that it offers a shorter time span, being available only since 2016. In our sensitivity analysis, we altered that threshold by using the top 5% and top 15%.

different from their conventional peers. Still, as discussed in Coqueret (2021), there is a lack of consensus regarding the rating of sustainable funds; this has led to the co-existence of different scores which, at times, can provide conflicting outcomes. While we do not present a complete picture of the ratings market, we hope to add valuable evidence to the debate on the actual specificity of ESG mutual funds through the lens of the score provided by a central actor. Extending the work to alternative scoring systems could be examined in future research. For the third of our building blocks, we used a news-based climate risk index recently proposed by Engle et al. (2020) to capture climate-related risk.[10] We further completed our database with traditional fund characteristics (e.g., returns, size, and age). In total, our database contains information on 2,042 unique mutual funds for the period 2013q1–2018q4, covering an average of 30% of assets under management (AUM) in the U.S. equity mutual fund market during the period studied.[11]

Our modeling strategy combines cross-sectional and panel regressions with interaction effects to characterize both time-varying and time-invariant patterns. First, using Fama and MacBeth (1973) analysis, we regressed our pairwise portfolio similarity metric ($PairwiseSimilarity$) (i) on a dummy variable that takes the value of one if at least one fund in the pair is high-ESG (to capture total portfolio similarity) in a first step, and (ii) on a dummy variable that takes the value of one if both funds in a pair are high-ESG (to capture intra-group portfolio similarity) and on a dummy variable that takes the value of one if one fund in the pair is high-ESG and the other one is conventional (to capture inter-group portfolio similarity) in a second step, as well as a set of controls that capture similarities within traditional fund attributes. The estimation procedure enabled us to test differences between portfolios at three levels: (i) intra-group (i.e., within both high-ESG mutual funds and conventional mutual funds), intergroup (i.e., between high-ESG mutual funds and conventional mutual

[10]Engle et al. (2020) constructed this index in order to develop a dynamic strategy that hedges news about climate change. Other studies, such as Ceccarelli et al. (2021), Huynh and Xia (2021), and Ilhan et al. (2021), have employed the index developed by Engle et al. (2020) to proxy climate change risks. While Ceccarelli et al. (2021) show that "low-carbon" labeled funds outperform conventional funds when the index increases, Ilhan et al. (2021) and Huynh and Xia (2021) investigate whether climate change news risk is priced in the options and corporate bonds market.

[11]Annual total AUM in the U.S. equity mutual fund market used for this estimate come from the annual ICI Fact Books from 2014 to 2019.

funds) and overall (e.g., high-ESG mutual funds vs all other funds) during each period (cross-sectional regressions) and across the whole sample (mean of cross-sectional estimates).
Second, using panel analysis with fund-level clustered standard errors, we regressed the financial performance of mutual funds measured by the four-factor alpha on a high-ESG dummy variable and state-of-the-art fund characteristics. Next, we interacted the dummy with the climate change risk index. Finally, we augmented our regression with another interaction term by adding the fund-specific distinctiveness metric (Distinctiveness). We repeated the same procedure in a last step by replacing four-factor alpha with fund flows. To assess the robustness of our findings, we conducted a sensitiveness analysis in which we altered several features of our baseline approach.

Our modeling dealt with a number of topics. The first question addressed was whether high-ESG and conventional mutual funds might hold different assets. Our estimation shows that the level of portfolio similarity between high-ESG and conventional mutual funds is lower than the average level in the market. Therefore, if we consider portfolio holdings, we can state that high-ESG mutual funds are actually different from their conventional peers. Interestingly, however, if we look more closely at how this feature has evolved over time, we notice that it tends to disappear. As time goes by, high-ESG and conventional funds are becoming increasingly similar.
The next question is whether the group of high-ESGs is fragmented or homogeneous. Nowadays, the ESG label is widely used and marketed to the general public by the funds themselves. Do these funds hold similar assets in their portfolios? And can we consider that they belong to the same investment style? In general, an investment style defines the general strategy of a set of funds, providing potential clients with simple information about what they can expect, for instance in terms of holdings. Taking the perspective of a regular client aiming to invest into a mutual fund with a sustainable focus, we now ask whether high-ESG investing could be somewhat assimilated to a traditional investment style by exploring the (dis-)similarity of portfolio holdings. Arguably, to be meaningful, a style should gather investment funds displaying both a high degree of homogeneity among style peers, compared to the rest of the market, and marked dissimilarity with other funds. Our results show that

high-ESG funds are quite different from each other. Indeed, they display a level of heterogeneity even higher than what can be observed on average in the market. This result is interesting, for we might have expected that within a smaller investment universe (owing to ethical constraints), such funds would display a high concentration of similar assets and a higher degree of homogeneity. On the other hand, this finding might reflect the fact that there exists a wide variety of approaches enabling fund managers to incorporate ESG issues into investment decisions, including: positive screening, negative or exclusionary screening, sustainability-themed investing, and impact investing, as well as many ways to implement each of these strategies and to combine them.[12] For mutual fund clients, this result implies that even among sustainable funds with high and relatively similar ESG scores, they may be confronted with funds whose portfolio compositions substantially differ; this affects the readability of this market segment. Nonetheless, if we examine the evolution of the pattern over time, we find that relative heterogeneity among ESG funds, as compared to conventional funds, tends to decrease. Growing homogeneity among high-ESG mutual funds might point to a maturing market.

If we shift to a systemic risk perspective, our results concerning portfolio similarity carry a couple of interesting implications. Portfolio similarity, as measured by overlap, is a source of systemic risk; this is caused by indirect exposure generated by two or more investors that have exposures in the same financial asset (e.g., Cerqueti et al., 2020; Delpini et al., 2019; Lavin et al., 2019). After documenting the overlap for specific segments of the industry, (i) between high-ESG and conventional mutual funds as well as (ii) within high-ESG funds, we now look at the system-wide overlap. Our results show that the level of portfolio similarity between a high-ESG mutual fund and all other funds in the market is, on average, lower than for conventional ones. This category might therefore contribute to mitigating systemic risk and foster market stability. From a fund for fund perspective, this result also shows that high-ESGs might provide interesting diversification opportunities. However, as stressed above, we can observe a time trend characterized, on the one hand, by increased homogeneity among high-ESG mutual funds and, on the other hand, by their holdings becoming more and more

[12] More information on these strategies can be found on a dedicated page on the US SIF website.

similar to those of conventional funds, suggesting that the dissimilarity feature tends to fade.

Our second topic dealt with differences between high-ESG and conventional mutual funds with respect to financial performance. Our baseline model, which looks at the unconditional effect of a high-ESG rating on financial performance, provides results consistent with the existing literature: On average, sustainable funds are shown to underperform their conventional peers (e.g., El Ghoul and Karoui, 2017; Renneboog et al., 2008a). This result is usually explained by the inclusion of ESG screening in investment decisions, which crowds out potentially lucrative investment opportunities and is eventually detrimental to the performance of ESG funds (see, for instance, Geczy et al., 2005; Renneboog et al., 2008a). However, this unconditional result may hide some heterogeneity. More specifically, several studies show that sustainable funds are more resilient than conventional ones in periods of crisis (e.g., Becchetti et al., 2015; Nofsinger and Varma, 2014; Pástor and Vorsatz, 2020). In essence, high-ESG mutual funds hold climate-friendly assets that should be better able to manage climate risk (e.g., Ardia et al., 2020; Choi et al., 2020; Engle et al., 2020). Our results confirm the greater resilience of ESG mutual funds when climate risk surges. In particular, we find that the performance of conventional funds is negatively affected in this context, while high-ESG mutual fund performance remains unchanged. At high levels of climate risk, however, there is no longer a significant performance gap between high-ESG funds and conventional funds.

As documented in the literature (Béreau et al., 2020; Sun et al., 2012; Vozlyublennaia and Wu, 2018), in addition to market conditions, another source of heterogeneity in financial performance among funds pertains to their distance from the average investment strategy. Since competition is likely to outweigh any potential abnormal return from a popular and easily imitated strategy (see Stein, 2008), fund managers are encouraged to "stand out from the crowd"—to quote Vozlyublennaia and Wu (2018). From this competition perspective, the implementation of distinctive investment strategies should allow funds to prevent competition and generate superior performance (Hoberg et al., 2018). While Sun et al. (2012) find evidence of a positive relationship between performance and investment strategy uniqueness in the hedge funds industry, Vozlyublennaia and Wu (2018) provide evidence that more distinctive funds charge higher fees but do not deliver a better net-of-fee performance in the mutual funds industry.[13]. Our findings indicate that, while portfolio distinctiveness does not affect the performance of conventional funds, it has a negative impact on the performance of high-ESG funds. These results highlight that, among high-ESG funds, those with less innovative strategies perform better. They further suggest that the level of portfolio distinctiveness influences the relative performance of high-ESG funds as compared to their conventional counterparts. At low levels of distinctiveness, high-ESG funds tend to significantly outperform. However, high-ESGs with very distinctive strategies perform badly and drive down the average results for the whole set of high-ESGs. This result holds over the whole period. If we interact the levels of both strategy distinctiveness and climate change risk, we provide much more nuanced conclusions: We find that the performance of less distinctive high-ESG mutual funds (i.e., core high-ESG) is negatively affected by climate risk. Therefore, mutual funds that were identified as having a lower performance over the whole period, be they high-ESG mutual funds in general (w.r.t. conventional mutual funds) or high-ESGs with the most distinctive strategy (w.r.t. core high-ESG mutual funds) are those performing best in times of crisis. This finding is consistent with a pattern observed in the literature: investors do tolerate underperformance in normal times if funds resist well in periods that are particularly important to them (Moskowitz, 2000, see also Pástor and Vorsatz, 2020 for ESG).

We also explored differences between high-ESGs and conventional mutual funds from the perspective of the capital flows that they attract from investors. Large-scale surveys (e.g., Krueger et al., 2020) and reports on sustainable investment trends (e.g., Morningstar, 2021; US SIF, 2020) show that the interest of investors in sustainability issues is growing. The general question we address at this stage is simply whether this interest translates into higher flows toward mutual funds with a sustainability focus and whether climate risk surges could act as a "wake-up call" and prompt investors to channel more capital toward this cate-

[13] Vozlyublennaia and Wu (2018) attributes these different findings to differences between the market structures of the hedge fund and mutual fund industries. In particular, they emphasize that mutual fund investors are smaller, less sophisticated and less constrained by share redemptions. Since mutual fund capital provision is more competitive, fund managers wield more market power and investors have less power to extract surplus provided by managerial skills.

gory of funds. Our results show that fund flows are, on average, influenced by climate risk changes. All things being equal, higher climate risk is associated with a larger number of flows, mainly toward less distinctive mutual funds. This result contradicts previous findings by Vozlyublennaia and Wu (2018), who concluded that mutual fund uniqueness did not influence flows. Regarding the ESG score, in our sample we could not identify any robust relationship between the sustainable focus of equity mutual funds and their flows at a one-quarter ahead horizon.

The rest of the paper is structured as follows: Section 2 describes our data and methodology. Section 3 discusses our results while Section 4 presents a series of robustness tests. Finally, Section 5 concludes our study.

2 Data and methodology

2.1 Data and sample

Our empirical analysis builds on an original database of U.S. equity mutual funds from 2013q1 to 2018q4. We collected fund-level information, including portfolio composition (i.e., holdings) and traditional characteristics, from the Morningstar Direct database. The latter is free of survival bias because it contains data on both active and dead funds; it is widely used in the mutual fund literature (see, for instance, Guercio and Tkac, 2008; Hartzmark and Sussman, 2019; Pástor and Vorsatz, 2020).

Following previous studies in the field (e.g., Ferreira et al., 2013; Kacperczyk et al., 2014, 2005), we applied several filters to our dataset. To keep our sample relatively homogeneous, we restricted it to active equity funds domiciled in the U.S., traded in U.S. dollars, and invested on the U.S. market. Whenever many shares of the same fund were available, we selected the oldest share identified by Morningstar to avoid multiple counting. We started with 3,172 U.S. equity mutual funds, and excluded index funds, exchange-traded funds, funds-of-funds, and funds with less than two quarters of holdings observations (Ferreira et al., 2013; Kacperczyk et al., 2014, 2005). Following Cremers and Petajisto (2009), we also left out funds with fewer than US$ 1 million of assets under management and under 60% of equity exposure. Finally, we filtered out funds for which sustainability information was not available. Our final sample includes 2,042 unique actively managed U.S. equity funds for the period 2013q1–2018q4.

We extracted traditional fund attributes from the Morningstar Direct database, such as returns, fund size (TNA), investment style (Morningstar Category), average manager tenure, sustainability score, and age measured in months since the inception of the oldest share. We also collected the annual net expense ratio (NER) and turnover ratio, both divided by four to obtain quarterly data. To complete our data, we computed volatility as the standard deviation of a fund's return estimated over the previous twelve months.

We followed the literature in defining fund net flows as the percentage growth in total TNA between two consecutive quarters (see Coval and Stafford, 2007).

$$Flows_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} * (1 + R_{i,t})}{TNA_{i,t-1}}$$

where $TNA_{i,t}$ and $R_{i,t}$ are the total net assets and the return of fund i at quarter t, respectively.

Finally, to capture fund abnormal returns, we estimated the traditional Carhart (1997) four-factor alpha[14] (e.g.,El Ghoul and Karoui, 2017; Ferreira et al., 2013).

$$r_{i,t} - r_t^f = \alpha + \beta_{MKT}(r_t^m - r_t^f) + \beta_{SMB} r_t^{SMB} + \beta_{HML} r_t^{HML} + \beta_{MOM} r_t^{MOM} + \epsilon_{i,t}$$

where $r_{i,t}$ is the net return of fund i on month t and r_t^f captures the one-month T-bill rate on the same month. $(r_t^m - r_t^f)$ corresponds to the excess return of the equity market in-

[14]This was done by using the previous 24 months of data, every quarter (complete return information over the window is required). The monthly U.S. factors and risk-free rate were retrieved from the Kenneth French online library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data library.html).

dex over the one-month T-bill rate, r_t^{SMB} is the difference of returns of a small-cap and a large-cap portfolio, r_t^{HML} denotes the difference of returns of portfolios made of high and low book-to-market stocks, and r_t^{MOM} stands for the momentum factor. Finally, α represents the risk-adjusted performance of fund i. To test the sensitivity of our results to this performance metric, we perform robustness tests using the five-factor alpha of Fama and French (2015).[15]

In what follows, we will discuss in more details three metrics that play a pivotal role in the rest of the analysis: (i) portfolio similarity, (ii) portfolio sustainability, and (iii) climate risk.

2.2 Measuring portfolio similarity and distinctiveness

One of the key elements of our analysis is the portfolio similarity (distinctiveness) metrics. In the literature on peer deviation, some authors, such as Sun et al. (2012) and Vozlyublennaia and Wu (2018), make use of market-based data; they compute the correlation of a fund's returns with the average returns of its peers. In contrast, a number of empirical papers employ units of measure based on portfolio holdings to assess the similarity of a fund relative to its peers. In particular, Cremers and Petajisto (2009) propose to evaluate peer deviation by assessing the share of portfolio holdings that differ from the benchmark index holdings. Kacperczyk et al. (2005) and Choi et al. (2017) both suggest comparing the shares of the portfolio invested in specific styles, industries or countries with the corresponding categories in the market portfolio. Although they are more difficult to access, holdings data provide more accurate information about portfolio similarity.

Like Cremers and Petajisto (2009), we use the Manhattan distance between holdings to

[15] As compared to the four-factor alpha (Carhart, 1997), the five-factor alpha (Fama and French, 2015) includes two "quality" factors, namely the profitability and the investment factors, and excludes the momentum factor, which has been proved to be important in empirical analysis. Recent research contributions have discussed the advantages and disadvantages of the different factor models (e.g., Blitz, 2016; Maiti, 2020). On this basis, and since the four-factor model remains standard in the literature (e.g., El Ghoul and Karoui, 2017; Price and Sun, 2017), we use the four-factor model in our baseline specification and we present the five-factor alpha analysis as a robustness test.

compute portfolio similarity.[16] To test the sensitivity of our results to this methodological choice, we perform robustness checks using cosine similarity.

For a pair of funds i and j at time t, we define the similarity between the two mutual fund portfolios of this pair as:

$$Pairwise\ Similarity_{ij,t} = 100 - \frac{1}{2}\sum_{m=1}^{M} |\omega_{im,t} - \omega_{j,mt}|$$

where $Pairwise\,Similarity_{ij}$ lies between 0 and 100, with no and full similarity between fund portfolios i and j. ω_{im} and ω_{jm} represent the portfolio weights of asset m in funds i and j, respectively. $\sum_{m=1}^{M} |\omega_{im} - \omega_{jm}|$ corresponds to the Manhattan distance between fund i and fund j across the stock universe M. In order to have an easily interpretable measurement of the overlap between two portfolios, we divide the Manhattan distance by 2 and subtract it from 100. If two portfolios perfectly overlap, the Manhattan distance is equal to 0 and the overlap value is 100.[17] In the opposite case, if the two portfolios have no overlap, the Manhattan distance is equal to 200 and the overlap value is equal to 0.

We aggregate the *Pairwise Similarity* metric at the fund level in order to capture the average similarity between one fund and all its peers.[18] The aggregate portfolio similarity between fund i at quarter t and the N other funds of the universe is given by:

$$Similarity_{i,t} = \frac{1}{N}\sum_{j\neq i}^{N} Pairwise\ Similarity_{ij,t}$$

Mirroring similarity metrics, we define distinctiveness metrics as follows:

$$Pairwise\ Distinctiveness_{ij,t} = 100 - Pairwise\ Similarity_{ij,t}$$

[16] Cremers and Petajisto (2009) compute the similarity between a fund and its benchmark by making use of the Manhattan distance between holdings.

[17] Like Cremers and Petajisto (2009), we do not count the long side and the short side of the positions separately.

[18] At each quarter, if our sample includes n funds, we end up with $\frac{n*(n-1)}{2}$ pairs of funds and therefore the same number of *Pairwise Similarity* observations.

If two portfolios perfectly overlap, the Manhattan distance and the distinctiveness value are equal to 0. In the opposite case, if the two portfolios have no overlap, the Manhattan distance is equal to 200 and the distinctiveness value is equal to 100. The average distinctiveness of one fund from all its peers is computed as:

$$Distinctiveness_{ij,t} = \frac{1}{N} \sum_{j \neq i}^{N} Pairwise\ Distinctiveness_{ij,t}$$

2.3 Measuring portfolio sustainability

A second key element of our study is the identification of sustainable funds. One strategy might entail relying on sustainability signals sent by fund managers—in fund prospectuses for instance. However, this first strategy's main drawback is that self-reported information may be strategically manipulated by mutual funds (see Hoberg et al., 2018; Sensoy, 2009 and Candelon et al., 2018 in the specific case of sustainability). In addition, prospectus analysis only provides time-invariant information that is qualitative rather than quantitative, making it difficult to compare one fund to another.

An alternative approach is to rely on ESG scores (or ratings) provided by third-party research firms. Although ESG scores also suffer from some weaknesses, such as a lack of harmonization between providers, they are widely accepted signals of the extent to which funds satisfy sustainability criteria (OECD, 2021). Today, the ESG ratings industry is diversified and includes major financial data providers (e.g., Bloomberg, MSCI, and Morningstar). We followed this second strategy and chose to rely on the Portfolio Sustainability Score compiled by Morningstar (with stock-level data provided by Sustainalytics) to capture the sustainability level of mutual funds. Morningstar is a leading provider of financial data, considered one of the most trusted sources of information in the mutual fund industry (e.g., Ben-David et al., 2019; Guercio and Tkac, 2008), and its sustainability metrics have frequently been used in recent mutual fund literature (e.g., Ammann et al., 2019; Candelon et al., 2021; Ceccarelli et al., 2021; Dolvin et al., 2019; Hartzmark and Sussman, 2019; Pástor and Vorsatz, 2020). Notably, Hartzmark and Sussman (2019) provide evidence suggesting that investors widely refer to Morningstar's sustainability ratings. Moreover, they cover a very large portion of the market, with more than 90% of U.S. equity funds included in our sample. Finally, among

ESG data providers Morningstar is the only one to provide historical ESG ratings at fund level, starting in 2012.

The Portfolio Sustainability Score developed by Morningstar is based on holdings and therefore reflects the sustainability level of the companies held in the fund portfolio.[19] The sustainability score of fund i at time t is computed as the asset-weighted sum of the difference between the ESG and Controversy scores of its holdings:

$$Sustainability\ Score_{i,t} = \sum_{m=1}^{M} \omega_{m,t}(ESG_{m,t} - Controversy_{m,t})$$

where ESG_m is the normalized company ESG score of firm m, $Controversy_m$ the controversy score of firm m, M is the number of assets held, and ω_m is the company's share of fund i's portfolio. The normalized company ESG score ranges from 0 to 100; it measures how a company compares to its industry peers on ESG issues according to a number of metrics regarding preparedness, disclosure, and performance relative to its industry peers. The Controversy score of a firm also ranges from 0 to 100 and captures a company's involvement in ESG-related controversial incidents. All company-level sustainability data is provided by Sustainalytics, a leading provider of sustainability research and ratings for investors. A fund receives a Portfolio Sustainability Score if company-level sustainability information is available for at least 67% of its assets under management. The score is updated monthly by Morningstar.

Using the Portfolio Sustainability Score, we divided mutual funds into two groups: high-ESG versus conventional. We ranked all of our funds on the basis of their sustainability score published each quarter and labeled funds among the top 10% of the distribution as "high-ESG." The others received the "conventional" label. We used this 10% threshold for two main reasons. First, it is broadly consistent with the proportion of self-declared sustainable mutual funds in our sample.[20] Second, the top 10% corresponds to the highest category

[19]Complete methodology can be found at `https://s21.q4cdn.com/198919461/files/doc_downloads/press_kits/2016/Morningstar-Sustainability-Rating-Methodology.pdf`

[20]Thanks to the "socially conscious" variable constructed by Morningstar by using mutual fund prospectuses, we identified 187 self-declared sustainable mutual funds in our sample (i.e., 9.2%). This data point is not time-varying so we only have a single data point for this variable for each fund.

of the fund-level Morningstar Sustainability Rating, also known as "Globe rating": A fund receives five globes and is rated "High" if its Portfolio Sustainability Score is in the top 10% for funds in the category.[21] This top 10% has been used in various studies to flag sustainable funds. For instance, Hartzmark and Sussman (2019) label "high sustainability" those funds that have received five globes; they provide evidence that the "high sustainability" classification is valued by investors.[22] To test the sensitivity of our results to this methodological choice, we modified this threshold by using the top 5% and the top 15% in our robustness checks.

2.4 Measuring climate change risk

The last key element of our analysis is the climate risk metric. Climate risk refers to the potential adverse economic and social effects of climate change; it can be divided into physical and transition risks (TCFD, 2017). Physical risk refers to damages inflicted by extreme weather events (e.g., droughts and storms) and long-term developments (e.g., rising temperatures and rising sea levels). Transition risk, also called regulatory risk, refers to costs that arise from policy, legal, technological, and business changes associated with the transition to a low carbon economy and is linked to public policy. While it is widely accepted that climate risk affects financial markets (e.g., Litterman et al., 2020), the literature that empirically examines these effects faces the challenge of measuring climate risk. Indeed, given the multidimensional nature of climate risk, it is difficult to create a single metric that would capture all of its aspects. Various strategies have been adopted to proxy this type of risk in recent literature (see Giglio et al., 2021 for a review), including the use of direct measurements of the underlying phenomenon (e.g., temperatures, rainfall, and sea level) or its drivers (e.g., greenhouse gases emissions, including CO_2), and of specific events related to climate disasters or policy action. An alternative approach to the assessment of climate risk as perceived by financial actors is news textual analysis (e.g., Ardia et al., 2020; Engle et al., 2020; Hsu and Wang, 2013; Santi, 2020). We adopted the latter strategy, drawing on

[21] Compared to the Portfolio Sustainability Score, the Globe rating has one major disadvantage: It offers a shorter time span, being only available from 2016.

[22] They show that being categorized as "high sustainability" led to substantial net inflows at the release of the rating.

a news-based climate risk index constructed and provided by Engle et al. (2020) that uses the Crimson Hexagon search engine to measure climate risk.

The Crimson Hexagon Negative Climate Change News Index (hereafter CHNEG Index) captures a climate news series through the textual analysis of influential news sources (e.g., The Wall Street Journal or The New York Times) and was used by Engle et al. (2020) to develop a dynamic strategy that hedges news about climate change.[23] The CHNEG index focuses on negative climate news, such that an increase in the index is associated with an increase in concern about climate change in the information media. As argued by Engle et al. (2020), this approach allows researchers to capture global climate risk from the perspective of financial actors because newspapers can be the primary source of information for investors updating their perceptions of climate risk. Moreover, it provides a continuous unit of measure with a reasonably long time horizon. Finally, this strategy provides a holistic approach to climate change risk, since it accounts for both its physical and transition components.[24] Other studies, such as Ceccarelli et al. (2021), Huynh and Xia (2021), Ilhan et al. (2021), recently used the index developed by Engle et al. (2020) to proxy climate change risk.[25]

2.5 Empirical settings

2.5.1 Portfolio composition

In the first part of our empirical analysis, we investigated the relationship between mutual fund sustainability and pair-level portfolio similarity. Specifically, we tested whether high-ESG mutual funds (i) might form a homogeneous group (ii) that is distinct from the rest of the market (**H1**), and we examined their overall portfolio overlap (i.e., both between and within groups).

[23] See Engle et al. (2020) for more details on the CHNEG index construction. The index provides us with data at a monthly frequency from May 2008 to May 2018. To match the frequency of our fund-level database, the CHNEG index data were aggregated to the quarterly level and, like Engle et al. (2020), we multiplied this value by 10,000 for ease of interpretation.

[24] The index covers news concerning physical damage caused by climate change on the one hand, and news about transition risks associated with climate change on the other.

[25] While Ceccarelli et al. (2021) show that “low-carbon” labeled funds outperform conventional funds when the index increases, Ilhan et al. (2021) and Huynh and Xia (2021) investigate whether climate change news risk is priced in the options and corporate bonds market, respectively.

To this end, we started by analyzing the portfolio similarity of high-ESG funds with respect to the overall market. To determine whether high-ESG funds are, on average, more similar to the market than their conventional peers, we estimated quarterly cross-sectional regressions of pairwise portfolio similarity for each fund pair's (*Pairwise Similarity*) on sustainability classification metrics and a set of other pair attributes (*Controls*).

$$\begin{aligned} Pairwise\,Similarity_{ij,t} = \beta_0 + \beta_1 High\,ESG_{ij,t} + \beta_2 CONV\&CONV_{ij,t} + \\ \sum_{c=1} \theta_c Controls_{ij,c,t} + \epsilon_{ij,t} \end{aligned} \tag{1}$$

where $High\,ESG_{ij}$ is a dummy variable that takes the value of 1 if at least one fund in the pair (i or j) is labeled "high-ESG," and 0 otherwise. $CONV\&CONV_{ij}$ is a dummy variable that takes the value of 1 if both funds in the pair (i and j) are conventional, and 0 otherwise. $Pairwise\,Similarity_{ij}$ is defined in Subsection 2.2. We imposed $\beta_2 = 0$, such that the base group is a pair of two conventional funds. The estimated value of β_1 provides the excess pairwise portfolio similarity of a pair containing at least one high-ESG fund compared to a pair consisting of two conventional funds.

Second, we investigated whether high-ESG funds might differ from their conventional peers and from each other. To this end, we estimated quarterly cross-sectional regressions of the pairwise portfolio similarity for each fund pair's (*Pairwise Similarity*) on sustainability classification metrics and a set of other pair attributes (*Controls*).

$$\begin{aligned} Pairwise\,Similarity_{ij,t} = \beta_0 + \beta_1 High\,ESG\&High\,ESG_{ij,t} + \beta_2 CONV\&CONV_{ij,t} + \\ \beta_3 High\,ESG\&CONV_{ij,t} + \sum_{c=1} \gamma_c Controls_{ij,c,t} + \epsilon_{ij,t} \end{aligned} \tag{2}$$

where $High\,ESG\&High\,ESG_{ij}$ is a dummy variable that takes the value of 1 if both funds in the pair (i and j) are high-ESG, and 0 otherwise, and $High\,ESG\&CONV_{ij}$ is a dummy variable that takes the value of 1 if one fund in the pair (i or j) is high-ESG and the other one (j or i) is conventional, and 0 otherwise. Again, we imposed $\beta_2 = 0$, such that the base group is a pair of two conventional funds. The estimated value of β_1 and β_3 provides the excess portfolio similarity of two high-ESG funds compared to a pair of two conventional funds and the excess portfolio similarity of a pair including one high-ESG and one conventional fund relative to a pair of two conventional funds, respectively. β_1 and β_3 allow us to discuss the first (i) and the second part (ii) of H1, respectively.

The ultimate goal of this empirical analysis was to find out how fund sustainability would affect pairwise portfolio similarity. Nevertheless, pairwise portfolio similarity may be related to the similarity of other fund characteristics. In the spirit of Cremers and Petajisto (2009), who studied the determinants of the distance between a fund's strategy and that of its benchmark, we included several fund attributes to control for their effects on similarity and isolate the sustainability effect in Equations 1 and 2. Controls included the product and the absolute difference of the following variables: number of holdings, the natural logarithm of the size and its squared value, flows, turnover ratio, net return and its volatility, age, expense ratio, and average manager tenure.[26] We further controlled for the belonging of funds to "traditional" investment styles.[27] We estimated Equations 1 and 2 for each quarter from 2013q1 to 2018q4 and reported the time-series average as in Fama and MacBeth (1973). To avoid autocorrelation in the time series of cross-sectional estimates, we performed inference using the Newey and West (1987) robust standard errors. We included serial correlation in our estimates up to a lag (i.e., one quarter).[28]

[26] All these controls are normalized (zero mean and unit standard deviation).

[27] Mutual funds usually invest in a restricted list of eligible assets, which defines their investment style and provides them with a simple tool to communicate their general strategy to their clients, eases the performance comparison with relevant peers, and enables them to concentrate their attention on a set of assets they know well (e.g. Almazan et al., 2004; Barberis et al., 2005; Brown and Goetzmann, 1997). To identify investment styles, we rely on the categorization provided by Morningstar, which classifies U.S. equities into common benchmark categories based on their size tilt (small-cap, mid-cap, or large-cap), value tilt (value, blend, or growth), and industry tilt (Communications, Consumer Defensive, Consumer Cyclical, Energy Limited Partnership, Equity Energy, Equity Precious Metals, Financial, Health, Industrials, Infrastructure, Natural Resources, Real Estate, Technology, and Utilities Miscellaneous Sector).

[28] This choice was motivated by the degree of autocorrelation found in the time series of coefficients: the partial serial correlation in the time series of regression coefficients associated with $High\,ESG$ in Equation 1 and $High\,ESG\&High\,ESG$ and $High\,ESG\&CONV$ in Equation 2 become statistically insignificant after one quarter. To ensure that this choice does not affect the results, we re-estimated our standard errors using larger lag lengths, and our results remain statistically significant

2.5.2 Financial performance

In the second part of our empirical analysis, we examined whether high-ESG funds might differ from their conventional peers in terms of the financial returns they provide to their investors, both unconditionally and conditionally to the level of portfolio distinctiveness and to the level of climate change risk. To this end, we estimated the general quarterly panel regressions with alternative settings:

$$
\begin{aligned}
\hat{\alpha}_{i,t} = \beta_0 &+ \beta_1 High\ ESG_{i,t-1} + \beta_2 Distinctiveness_{i,t-1} + \beta_3 CHNEG_{t-1} + \\
&\beta_4 High\ ESG_{i,t-1} * Distinctiveness_{i,t-1} + \beta_5 High\ ESG_{i,t-1} * CHNEG_{t-1} + \\
&\beta_6 Distinctiveness_{i,t-1} * CHNEG_{t-1} + \\
&\beta_7 High\ ESG_{i,t-1} * Distinctiveness_{i,t-1} * CHNEG_{t-1} + \\
&\sum_{c=1} \gamma_c Controls_{i,c,t-1} + S_i + Q_t + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

where $\hat{\alpha}_{i,t}$ is the estimated net four-factor alpha of fund i at time t, $High\ ESG_{i,t-1}$ is a dummy variable that takes the value of 1 if fund i is flagged "high-ESG" at time $t1$, and 0 otherwise. $Distinctiveness_{i,t-1}$ captures the average portfolio distinctiveness of fund i at quarter $t-1$, and $CHNEG_{t-1}$ corresponds to the Crimson Hexagon Negative Climate Change News Index. All these variables are defined and described in Section 2 (Subsections 2.1 to 2.4). Given the availability of the CHNEG index, the panel regressions were estimated on quarterly data from 2013q1 to 2018q2. Robust standard errors are clustered at the fund-level to account for autocorrelation in fund performance.

First, we examined whether high-ESG mutual fund performance might differ from conventional performance on average (**H2**). To this end, we regressed the net four-factor alpha on the $High\ ESG$ dummy and set $\beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$. The coefficient of the $High\ ESG$ dummy, β_1, captures the difference between high-ESG and conventional risk-adjusted returns. We controlled for a number of traditional fund attributes that have been shown in the literature to determine performance, including fund flows and volatility, volatility of net returns, fund size, number of holdings, turnover ratio, expense ratio, R^2 of four-factor regression, and age[29] (see, for instance, Amihud and Goyenko, 2013; Cremers and Petajisto, 2009; El Ghoul and Karoui, 2017; Ferreira et al., 2013). Finally, like El Ghoul and Karoui (2017), we added fixed effects for style (S) and time (Q) to account for cross-sectional dependence.

Second, we tested whether high-ESG mutual funds might differ from their conventional peers in terms of financial returns, conditionally to the level of distinctiveness of their portfolio (**H3**). To do so, we regressed the net four-factor alpha on the $High\ ESG$ dummy, the $Distinctiveness$ variable and their interaction, and imposed $\beta_3 = \beta_5 = \beta_6 = \beta_7 = 0$. The coefficient of the $Distinctiveness$ variable, β_2, captures the impact of the level of portfolio distinctiveness on the performance of conventional funds, while the coefficient of the interaction term $High\ ESG * Distinctiveness$, β_4, captures whether and to what extent this impact differs for high-ESG funds. As in the previous setting, we controlled for traditional fund characteristics, and included style and time fixed effects.

Third, we investigated whether high-ESG funds might be viewed as a hedge against climate change risk (**H4**). To this end, we regressed the net four-factor alpha on the $High\ ESG$ dummy, the $CHNEG$ variable and their interaction, and imposed $\beta_2 = \beta_4 = \beta_6 = \beta_7 = 0$. The coefficient of the $CHNEG$ variable, β_3, captures the impact of the climate risk index CHNEG on the performance of conventional funds, while the coefficient of the interaction term $High\ ESG * CHNEG$, β_5, captures whether and to what extent this impact differs for high-ESG funds. As in the previous two specifications, we controlled for traditional fund characteristics and included style effects. Since this specification includes the $CHNEG$ variable, which only varies across time but not across funds, we did not include time fixed effects. To capture the general state of the market, we added the quarterly S&P 500 index to our model.

Finally, without constraining the coefficients, our model allowed us to test whether high-ESG funds that follow more unique investment strategies might provide a better hedge

[29]The continuous variables are winsorized at the 1% level to avoid outliers.

against climate change risk (**H5**). We regressed the net four-factor alpha on the $High\,ESG$ dummy, the $CHNEG$ variable, the $Distinctiveness$ variable, and their interactions. The coefficient of $CHNEG$, β_3, captures the impact of climate risk on the performance of the conventional fund with the least distinctive portfolio, while the coefficient of the $High\,ESG * CHNEG$ interaction term, β_5, captures whether and to what extent this impact differs for a high-ESG fund and the least distinctive portfolio. The coefficient of the interaction term $Distinctiveness * CHNEG$, β_6, indicates whether the level of portfolio distinctiveness affects the sensitivity of conventional performance to climate change risk, while the coefficient of the interaction term $High\,ESG * Distinctiveness * CHNEG$, β_7, captures whether and to what extent this impact differs for high-ESG funds. As with the third specification, we controlled for traditional fund characteristics, and included style effects and the quarterly S&P 500.

2.5.3 Flows

In the last part of our empirical analysis, we examined whether high-ESG funds might differ from their conventional peers in terms of the net capital flows they attract from their investors, unconditionally and conditionally to the level of portfolio distinctiveness and to the level of climate change risk. To this end, we estimated the general quarterly panel regressions with alternative specifications:

$$\begin{aligned} Flows_{i,t} = \beta_0 &+ \beta_1 High\,ESG_{i,t-1} + \beta_2 Distinctiveness_{i,t-1} + \beta_3 CHNEG_{t-1} + \\ &\beta_4 High\,ESG_{i,t-1} * Distinctiveness_{i,t-1} + \beta_5 High\,ESG_{i,t-1} * CHNEG_{t-1} + \\ &\beta_6 Distinctiveness_{i,t-1} * CHNEG_{t-1} + \\ &\beta_7 High\,ESG_{i,t-1} * Distinctiveness_{i,t} * CHNEG_{t-1} + \\ &\sum_{c=1} \gamma_c Controls_{i,c,t-1} + S_i + Q_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

These alternative specifications are similar to the four settings presented for the performance analysis. In particular, we tested whether acute interest in sustainable investment had resulted in a reallocation of capital from conventional funds to high-ESG funds in recent years (**H6**). In addition, we investigated whether climate risk has been acting as a wake-up call on sustainability issues and has influenced investors to reallocate capital toward high-ESG funds when climate concerns surge (**H7**). In the specifications, we included controls for a number of traditional fund characteristics such as: fund performance and its volatility, volatility of net returns, fund size, number of holdings, turnover ratio, expense ratio, R^2 of the four-factor regression, and age[30] (e.g., Ammann et al., 2019; Ceccarelli et al., 2021; El Ghoul and Karoui, 2017; Ferreira et al., 2012; Franzoni and Schmalz, 2017). As with the performance analysis, we added fixed effects for style (S) and time (Q) to account for cross-sectional dependence (El Ghoul and Karoui, 2017), except for specifications including the $CHNEG$ variable, in which we included the SP 500 index instead of fixed effects for time. Robust standard errors are clustered at the fund level to account for autocorrelation in fund performance.

3 Results

3.1 Descriptive statistics

- Table 1 -

Table 1 shows the time-series average of cross-sectional summary statistics for the main variables in our sample over the period 2013q1–2018q4. On average, our sample includes 1,483 mutual funds per quarter, with a standard deviation of 202 funds. The average portfolio distinctiveness between a fund and its peers is 90.89, with a minimum of 89.21 and a maximum of 92.83. As a reminder, our distinctiveness metric was constructed in such a way that two portfolios that do not overlap would receive a score of 100, while two perfectly similar portfolios would receive a score of 0. The sustainability score ranges from 43.23 to 48.41, with an average of 45.91. On average, the funds in our sample manage US$ 1.77 billion in assets and are 18 years old. The mean quarterly net flow (-0.55%) reflects a slowdown in the mutual fund industry over the period studied, and the volatility over the previous 24 months is 3.39%. The average annual NER is about 1%, while the quarterly turnover

[30]The continuous variables are winsorized at the 1% level to avoid outliers.

is about 14.52%. The mean quarterly net return is 2.55%, the median is 4.55%, and the volatility of net returns over the previous 24 months is 3.47%. On average, the funds in our sample hold 117 assets in their portfolios. Consistent with the inability of active funds to create value, which is well-documented in the literature, the quarterly net abnormal performance (four-factor alpha) is negative on average (-0.33%). Finally, the average R2 of the four-factor alpha regression is 89.18%, implying that most of the variability in average fund returns is explained by the Carhart (1997) four-factor model (Amihud and Goyenko, 2013).

- Table 2 -

In Table 2, we compare the descriptive statistics of the high-ESG group with those of the conventional group. We observe that, on average, sustainable funds tend to be larger and have a lower turnover ratio than their conventional counterparts. Although high-ESG funds hold a significantly lower number of assets in their portfolios, the volatility of their returns is not significantly different from that of their conventional counterparts. While the average portfolio distinctiveness of high-ESGs does not appear to differ from that of their conventional peers, at the pair level we find that two high-ESG funds are more similar in terms of their portfolio holdings than a high-ESG and a conventional fund. Even if their flows do not differ, those of high-ESGs seem to be more stable than those of conventional funds. Finally, the performance of high-ESG funds is not statistically different from that of their conventional peers, even if they have a lower R^2, suggesting a higher degree of equity selectivity, without accounting for additional characteristics.

3.2 Portfolio composition

- Table 3 -

Table 3 presents the results of cross-sectional variation in pairwise portfolio similarity. The full table, including all controls, can be found in Appendix A. Column (1) of this table reports the Fama and MacBeth (1973) estimates of the quarterly cross-sectional regression of pairwise fund similarity on a dummy variable that takes the value of 1 if at least one fund in the pair is designated as high-ESG ($High\,ESG$), as well as controls that capture similarities between the two funds of the pair in terms of other fund attributes (Equation 1). It appears that *High ESG* is highly statistically significant, with a coefficient of -1.2346 (t=-14.64). Once we control for the similarity of other characteristics, portfolio similarity within a pair of two funds, at least one of which is high-ESG, is lower than the similarity within a pair of two conventional funds. This result is consistent with that of Cerqueti et al. (2020), who find low total portfolio overlap (i.e., high-ESG funds with the overall market), and implies that high-ESG funds could reduce systemic risk and foster market stability, despite the concentration of their portfolios on a more limited number of assets (e.g., Barnett and Salomon, 2006; Renneboog et al., 2008b). From a fund-of-fund perspective, our results also indicate that they could provide interesting diversification opportunities.

Figure 1: Time series of the Fama and MacBeth (1973) estimated coefficients

Panel A | Panel B

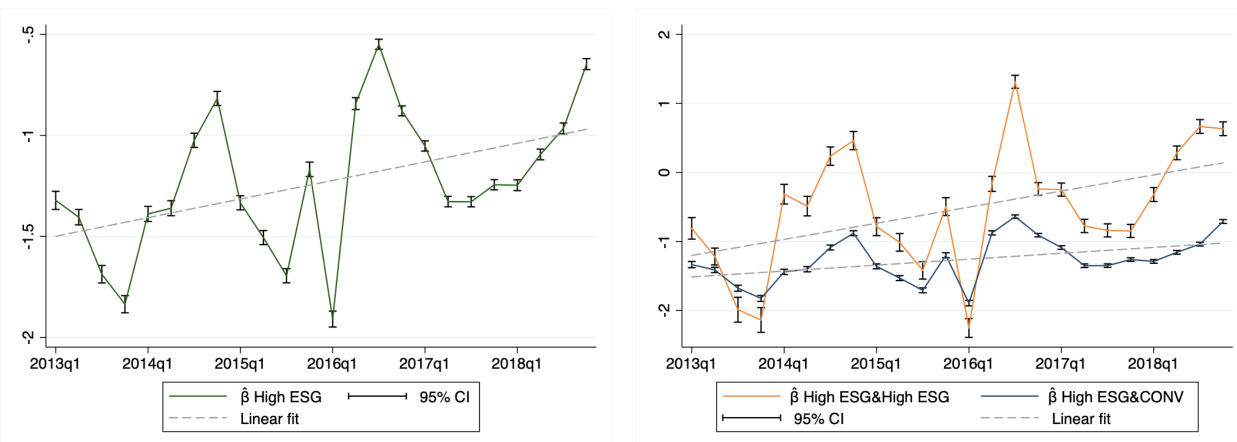

Figure 1 reports the time series of the Fama and MacBeth (1973) estimated coefficients associated with (i) *High ESG* - (column (1) from Table 3) in Panel A, (ii) *High ESG&High ESG* and *High ESG&CONV* (column (2) from Table 3) in Panel B, the 95% confidence intervals associated with these coefficients, and linear time trends fitted in these time series.

Panel A of Figure 1 plots the time series of Fama and MacBeth (1973) coefficients associated with *High ESG* and their 95% confidence interval for each quarter. We observe that the coefficient evolves over time, which nuances the conclusions drawn earlier. When we plot linear fits in the time series of coefficients associated with *High ESG*, we find an upward trend in the series. Despite this upward trend, the coefficient remains significantly negative over the entire period.

Column (2) of Table 3 reports the Fama and MacBeth (1973) estimates of the quarterly cross-sectional regression of the pair of funds' similarity on a dummy variable that takes the value of 1 if both funds in the pair are labeled high-ESG ($High\ ESG\&High\ ESG$) and a dummy variable that takes the value of 1 if one fund in the pair is labeled high-ESG and the other as conventional ($High\ ESG\&CONV$), as well as controls that capture similarities between the two funds of the pair in terms of other fund attributes (Equation 2). The estimated coefficient of $High\ ESG\&CONV$ is -1.2683 and highly statistically significant (t=-16.09). Once we control for the similarity of other characteristics, portfolio similarity within a pair of one high-ESG and one conventional fund is lower than the similarity within a pair of two conventional funds. This result suggests that, if we base our analysis on portfolio holdings, high-ESG mutual funds are actually different from their conventional peers, which corroborates the second part (ii) of H1. This finding is in the same vein as what Joliet and Titova (2018) found: High-ESG funds target their portfolios toward high-ESG assets and, as a result, exploit a market segment that is not tapped by the rest of the industry. In addition, we find that $High\ ESG\&High\ ESG$ is highly statistically significant with a coefficient of -0.5324 (t=-2.46), which implies that portfolio similarity within a pair of two high-ESGs is lower than the similarity within a pair of two conventional funds. This result indicates that the high-ESG group appears to be less homogeneous than the conventional group, which does not support the first part (i) of H1. This finding is quite surprising since we might have expected that, operating in a smaller investment universe (owing to ethical constraints), such funds would have displayed a high concentration of similar assets and, thus, a high degree of homogeneity. From the perspective of mutual fund clients, it seems important to consider this feature of the market segment because it means that they may be exposed to players holding a wide variety of portfolios under similar ESG scores.

Panel B of Figure 1 displays the time series of Fama and MacBeth (1973) coefficients associated with $High\ ESG\&High\ ESG$ and $High\ ESG\&CONV$, as well as their 95% confidence interval for each quarter. It appears that heterogeneity within high-ESG funds, as well as the difference between high-ESGs and conventional funds, has evolved over time. The conclusions we draw from the analysis of cross-sectional variation in portfolio similarity may therefore be balanced. The distinctiveness of high-ESG funds—both among themselves and compared to conventional funds—seems to be decreasing over time. If we linearly fit the time series of coefficients for $High\ ESG\&High\ ESG$ and $High\ ESG\&CONV$, we observe an upward trend in both series. Despite the slight upward trend, the similarity between a conventional and a high-ESG fund is significantly lower than the similarity between two conventional funds throughout the period. This is not the case for the $High\ ESG\&High\ ESG$ coefficients. Apart from a few isolated peaks (2014q3,q4 and 2016q3), we find that the coefficients become significantly positive from the second quarter of 2018 onwards, implying that two high-ESG funds become more similar to each other than two conventional funds. Thus, it appears that the similarity of high-ESG funds in terms of portfolio composition has increased significantly over the years.

3.3 Financial performance

- Table 4 -

Table 4 gathers the results of the quarterly panel regressions (2013q1–2018q2) of Equation 3 with alternative settings. The first column reports the results of the baseline model, with $\beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$, which allows us to test whether high-ESGs differ from conventional funds in terms of financial performance. On the one hand, incorporating ESG criteria into investment decisions crowds out potentially profitable investments, which is detrimental to the performance of ESG funds (e.g., Geczy et al., 2005; Renneboog et al., 2008b). On the other hand, these screening criteria should allow fund managers to select better-managed companies with strong fundamentals, which should have a positive impact on performance. These two effects compete and the outcome depends on their relative strengths. Our result supports the first one; indeed, the estimated coefficient of the $High\ ESG$ dummy variable dummy variable is negative and statistically significant at the 5% level (-0.0675, t=-2.39), suggesting that, once we control for the influence of other fund characteristics, the high-ESG funds in our sample underperform their conventional peers on average. This result is consistent with existing empirical works that provide evidence of the weak performance of socially responsible funds compared to their peers (see, for instance, El Ghoul and Karoui, 2017; Renneboog et al., 2008a) and supports H2, that is, high-ESGs differ from their conventional peers in terms of the financial returns they provide to their investors.

As for the control variables, our results are generally in line with the existing literature. We find that turnover ratio and NER are negatively associated with future risk-adjusted returns, as in Carhart (1997). Excess turnover can increase transaction costs, which ultimately lowers profitability for investors. Similarly, fund managers who charge higher fees lower the value of the investment. Consistent with Cremers and Petajisto (2009) and Amihud and Goyenko (2013), we find a negative relationship between fund age and future performance. Moreover, it appears that older funds tend to have worse abnormal returns. As in Amihud and Goyenko (2013), we represent the manager's "stock selectivity" by the R^2 of the factor performance regression and find that higher stock selectivity (a decrease in R^2) positively affects performance. Our results also suggest that excessive volatility is detrimental to risk-adjusted returns. In support of Gruber (1996) and the smart money effect, capital flows are positively related to four-factor alpha. Finally, the natural logarithm of the number of stocks has no explanatory power for future performance.

Figure 2: Conditional marginal effects of $High\ ESG$ on $\hat{\alpha}$

Panel A

Panel B

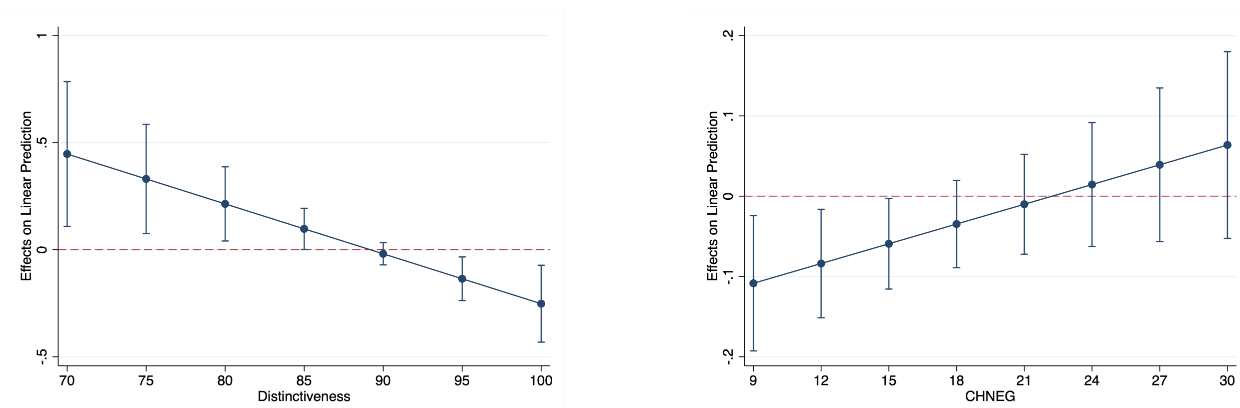

Figure 2 presents the marginal effects of $High\ ESG$ (discrete change from 0 to 1) on $\hat{\alpha}$ conditional to the level of (i) portfolio distinctiveness ($Distinctiveness$) in Panel A, and (ii) climate change risk ($CHNEG$) in Panel B.

In the second column of Table 4, we extend our baseline model to include the level of portfolio distinctiveness ($Distinctiveness$) and its interaction with the high-ESG dummy variable ($High\ ESG * Distinctiveness$) in order to test whether the average weak performance of high-ESG funds hides any heterogeneity relative to investment strategy uniqueness. To this end, we estimate Equation 3 and set $\beta_3 = \beta_5 = \beta_6 = \beta_7 = 0$. In this second specification, for a level of portfolio distinctiveness close to 0, the least unique high-ESG fund outperforms its conventional counterpart, as shown by a positive and significant coefficient estimate on $High\ ESG$ (1.6562, t=2.08). However, our results suggest that this strong relative performance of high-ESG funds declines as funds implement more unique investment strategies. Indeed, the level of distinctiveness does not significantly affect the future alpha of conventional funds (-0.0053, t=-1.47), consistent with Vozlyublennaia and Wu (2018), who find that mutual funds "standing out from the crowd" do not deliver better net-of-fee performance, while it lowers the future performance of high-ESG funds (-0.0189, t= -2.13): a one-unit standard deviation increase in the level of portfolio distinctiveness lowers the future performance of high-ESG funds by 0.0791 (-0.0189*4.1749). Panel A of Figure 2, which plots the marginal effect of high-ESGs on financial performance as a function of the level of portfolio distinctiveness, illustrates this feature graphically. Our results indicate that high-ESGs with very distinctive strategies perform badly compared to their conventional peers and drive down the average results for the whole set of high-ESGs. They validate H3, that is, the unconditional poor performance of high-ESG funds hides their heterogeneity, with more distinctive high-ESGs the most underperforming relative to their conventional peers.

The third column of Table 4 reports the results of our baseline model augmented with the climate risk index ($CHNEG$) and its interaction with the high-ESG dummy variable ($High\ ESG * CHNEG$). We estimate Equation 3 and set $\beta_2 = \beta_4 = \beta_6 = \beta_7 = 0$.[31] This third specification allows us to account for the effect of climate change risk on the performance difference between high-ESGs and conventional funds. For a level of climate risk close to 0, we find that high-ESG funds strongly outperform their conventional peers (-0.2172, t=-2.67). The coefficient estimate of $CHNEG$ is negative and highly significant (-0.0094, t=-9.06), implying that an increase in climate change risk worsens the future performance of conventional funds: a one-unit standard deviation increase in the CHNEG index

[31] Since this specification includes the $CHNEG$ variable, which only varies across time but not across funds, we do not include time fixed effects. To capture the general state of the market, we add the quarterly S&P 500 index to our model.

decreases the future alpha of conventional funds by 0.0632 (-0.0094*6.7227). As theoretical and empirical works suggest, climate-friendly assets are better climate hedges (e.g., Ardia et al., 2020; Choi et al., 2017; Engle et al., 2020). Therefore, we can expect funds that hold such assets to be more able to manage climate risk. Supporting this argument, we find that the coefficient of the interaction term $High ESG * CHNEG$ is positive and significant at the 5% level (0.0085, t=2.06), meaning that the negative effect of climate risk on future performance observed for conventional funds is lower for high-ESG funds. Therefore, our findings suggest that this weak relative performance lessens as climate risk surges. Panel B of Figure 2, which plots the marginal effect of high-ESGs on financial performance as a function of climate change risk, illustrates this feature graphically. In particular, we observe that there is no longer a significant difference in performance between high-ESG funds and conventional funds at high levels of climate risk. Our findings support H4, that is, the financial returns of high-ESGs and conventional funds are affected differently by climate risk, suggesting that high-ESG funds are more resilient to climate risk. Our results complement previous studies showing that sustainable funds are more resilient in crisis periods (e.g., Becchetti et al., 2015; Nofsinger and Varma, 2014; Pástor and Vorsatz, 2020) and support the popular hypothesis that investors do tolerate underperformance during normal times if their funds outperform during times that matter the most to them (Moskowitz, 2000).

Finally, we estimate our baseline model without any restriction on coefficients.[32] Results of this specification are reported in column (4) of Table 4. The coefficient estimate of $Distinctiveness * CHNEG$ is positive and statistically significant at the 1% level (0.0008, t=3.33), which means that the portfolio level of distinctiveness mitigates the sensitivity of conventional performance to climate change risk and, therefore, that more unique mutual funds are more resilient to climate risk. The positive and statistically significant coefficient of $High\ ESG * Distinctiveness * CHNEG$ (0.0053, t=4.52) indicates that this mitigating effect is stronger for high-ESG funds. As regards high-ESG funds, our model predicts a positive impact of climate change risk on performance for most distinctive funds. Indeed, the

[32]Since this specification includes the $CHNEG$ variable, which only varies across time but not across funds, we do not include time fixed effects. To capture the general state of the market, we add the quarterly S&P 500 index to our model.

conditional marginal effect of CHNEG on the performance of high-ESG funds with a level of portfolio distinctiveness in the top quartile is positive (0.0219, z=3.04), that is, a one-unit standard deviation increase in the CHNEG index increases future performance of the most distinctive high-ESG funds by 0.1474. This finding corroborates H5, that is, high-ESG funds that follow more unique investment strategies provide a better hedge against climate change risk.

In summary, we find that on average high-ESG mutual funds underperform their conventional peers. This suggests that investors seeking to invest into funds that best meet ESG criteria have had to sacrifice returns in recent years in order to achieve their objectives. Moreover, we show that the difference between high-ESG and conventional risk-adjusted returns is related to climate risk. When climate risk increases, the performance of conventional funds decreases, while the performance of high-ESG funds is unaffected, which reduces the performance gap between high-ESGs and conventional funds. Under extreme climate risk, our results suggest that the former can outperform the latter, implying that high-ESG funds hedge climate risk. Finally, it appears that, among high-ESG funds, the most resilient to climate change are those that hold the most unique portfolio.

3.4 Flows

- Table 5 -

Table 5 presents the results of the quarterly panel regressions (2013q1–2018q2) of Equation 4 with alternative settings. Column (1) reports the results of the baseline model, with $\beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$, which allows us to test whether high-ESGs differ from conventional funds in terms of capital flows. The estimated coefficient of the dummy variable $High\ ESG$ is not significantly different from 0 (-0.0536, t=-0.23) and provides no evidence that high-ESG mutual funds differ from their conventional counterparts in terms of the capital flows that they attract when we control for other fund characteristics. This finding does not support H6, that is, acute interest in sustainable investing has led to a reallocation of capital from conventional funds to high-ESG funds in recent years. While our result is in line with the work of El Ghoul and Karoui (2017), who find that U.S. equity fund flows are not affected by either a fund's social responsibility score or a SRI dummy, it contrasts with existing studies that show that socially responsible funds tend to attract higher capital flows than their conventional counterparts in earlier periods (e.g., Benson and Humphrey, 2008; Bialkowski and Starks, 2016; Bollen, 2007). A likely explanation for this divergence is that investors have already aligned their investments with their ethical values and the reallocation of capital to sustainable funds took place in the early 21st century. More recently, empirical work has shown that investors respond to the release of new ESG-related ratings and labels even if sustainability information was already available earlier (e.g., Ammann et al., 2019; Ceccarelli et al., 2021; Hartzmark and Sussman, 2019), which may suggest that investors only react to newly available sustainability signals in an ad hoc manner.

With regard to control variables, we find that past risk-adjusted returns positively predict future flows (e.g., Ammann et al., 2019; Ceccarelli et al., 2021; El Ghoul and Karoui, 2017; Ferreira et al., 2012; Franzoni and Schmalz, 2017). Like El Ghoul and Karoui (2017), we find no significant explanatory power of the number of holdings for fund flows. Furthermore, our results suggest that funds that experience more volatile flows attract more flows. In line with Ammann et al. (2019) and El Ghoul and Karoui (2017), NER is significantly and negatively related to flows. Ferreira et al. (2012) find a negative but non-significant relationship between fund fees and flows. In addition, our findings show that the oldest funds, as well as those having a lower turnover ratio, attract lower flows (Ceccarelli et al., 2021; Franzoni and Schmalz, 2017).[33] Concerning fund size, we find a negative and significant relationship between the natural logarithm of the size and flows (e.g., Ammann et al., 2019; Ceccarelli et al., 2021; El Ghoul and Karoui, 2017; Ferreira et al., 2012; Franzoni and Schmalz, 2017). Consistent with El Ghoul and Karoui (2017), we find no explanatory power of the R2 for fund flows. Eventually, we provide evidence suggesting a positive relationship between net returns volatility and flows.

[33] Regarding age, Ammann et al. (2019) and El Ghoul and Karoui (2017) also find a negative but non-significant relationship. Ammann et al. (2019) find a negative but insignificant impact of turnover ratio on flows while El Ghoul and Karoui (2017) find a positive and weakly significant relationship.

In the second column of Table 5, we augment our baseline model with the level of portfolio distinctiveness (*Distinctiveness*) and its interaction with the high-ESG dummy ($High\,ESG *$ *Distinctiveness*) to investigate whether investment strategy uniqueness affects high-ESG and conventional fund flows. We estimate Equation 4 with $\beta_3 = \beta_5 = \beta_6 = \beta_7 = 0$. The estimated coefficients of *Distinctiveness* and $High\,ESG * Distinctiveness$ are not statistically significant at the 10% level (0.0093, t=0.24, and -0.0772, t=-1.33, respectively). These results suggest that implementing a more unique investment strategy is not rewarded by higher capital flows, regardless of the high-ESG status, and are consistent with Vozlyublennaia and Wu (2018), who find no significant relationship between flows and strategy uniqueness in the mutual fund industry.

The third column of Table 5 reports the results of our baseline model extended by the CHNEG index and its interaction with the *High ESG* dummy to investigate whether climate risk acts as a "wake-up call" to investors, leading them to reallocate their capital to sustainable funds when climate risk surges.[34] Sudden capital flows to high-ESG funds, that hold few assets and invest into a limited universe, could pose a concentration risk, potentially leading to liquidity risks in the event of an unexpected sell-off. The question of capital reallocation in response to climate risk is central for regulators on the one hand, and for policymakers, whose decisions may directly influence the "transition" component of climate risk, on the other.[35]. To investigate this question, we estimate Equation 4 with $\beta_2 = \beta_4 = \beta_6 = \beta_7 = 0$.[36] The estimated coefficient of $CHNEG$ is positive and statistically significant at the 10% level (0.0226, t=1.84). Therefore, it appears that conventional funds attract more flows when climate risk increases: a one-unit standard deviation increase in the CHNEG index increases future flows of conventional funds by 0.1519 (0.0226* 6.7225). As

[34]The notion of "wake-up call" refers to a situation in which new information causes investors to reassess the value of their assets. This notion was first used by Goldstein et al. (1998) in the context of the Asian financial crisis, and has been studied by several authors in different contexts since then (e.g., Bekaert et al., 2014).

[35]See the speech ILB Brief : Green and Sustainable Finance series by Jean Boissinot, Head of Secretariat of the Network for Greening the Financial System (NGFS) and Deputy Director for Financial Stability at the Bank of France (2021/12/10).

[36]Since this specification includes the $CHNEG$ variable, which varies only over time, not across funds, we do not include time fixed effects. To capture general market conditions, we add the quarterly S&P 500 index to our model.

the coefficient of the interaction term $High\, ESG * CHNEG$ iis not statistically significant at the 10% level (0.0043, t=0.15), our results provide no evidence suggesting that this effect differs for high-ESG funds. These results do not support H7—that is, investors reallocate capital from conventional funds to high-ESG funds when climate concerns surges—since they suggest that investors invest more capital into both high-ESG and conventional mutual funds when climate risk increases.

Finally, we estimate our baseline model without any restriction of the coefficients.[37] The fourth column of Table 5 presents the results of this specification. We observe that the coefficient estimate of $Distinctiveness * CHNEG$ is negative and statistically significant at the 1% level (-0.0073, t=-2.73). This result indicates that the positive impact of climate risk on conventional fund flows is lower for funds with more unique investment strategies. Since the coefficient of the interaction term $HighESG * Distinctiveness * CHNEG$ is not statistically different from zero at the 10% level (0.0020, t=0.28), our results provide no evidence that this effect is different for high-ESG funds.

In summary, we find that, on average, fund flows are affected by changes in climate risk. All things being equal, higher climate risk is associated with higher capital flows, mainly into mutual funds with less distinctive investment strategies. Finally, regarding the ESG score, we cannot identify any robust relationship in our sample between the sustainable focus of equity mutual funds and their flows.

4 Robustness checks

4.1 Portfolio composition

To confirm our results concerning portfolio similarity, we re-estimate the two main models—Equations 1 and 2—with alternative settings. In a first step, we consider an alternative

[37] Since this specification includes the $CHNEG$ variable, which only varies across time but not across funds, we do not include time fixed effects. To capture the general state of the market, we add the quarterly S&P 500 index to our model.

metric to assess pairwise similarity. In a second step, we estimate our model using a subsample of survivors. Finally, we propose two different definitions of high-ESG thresholds.

First, we consider an alternative approach to measuring pairwise similarity in order to test the sensitivity of our results to the definition of our dependent variable. In the main specifications, our metric of pairwise similarity is based on the Manhattan distance between the portfolio holdings of each paired fund (Cremers and Petajisto, 2009). We redefine this metric by making use of the Euclidean distance. In particular, we compute the similarity between two portfolios i and j at quarter t as:

$$Pairwise\ Similarity\ alt_{ij,t} = \frac{h_{i,t} \cdot h_{j,t}}{|h_{i,t}||h_{j,t}|}$$

This metric represents the cosine of the angle between two mutual fund portfolio vectors in security space. Cosine similarity has been used in the mutual funds literature to capture portfolio overlap (see, for instance, Blocher, 2016; Delpini et al., 2019; Fricke, 2019; Girardi et al., 2020; Nanda and Wei, 2018). It lies between 0 and 1, for no and full overlap between two portfolios i and j, respectively. $Pairwise Similarity alt_{ij}$ is computed as the dot product between two portfolio vectors h_i and h_j divided by the product of the Euclidean norm of each vector.

For fund i at quarter t, the Euclidean norm is defined across M securities as:

$$|h_{i,t}| = \sqrt{\sum_{m=1}^{M} h_{im,t}^2}$$

- Table 6 -

Columns (1) and (2) of Table 6 replicate the two models—columns (1) and (2) of Table 3, respectively—using this alternative definition of pairwise similarity. In the first specification, *High ESG* is negative and highly statistically significant, with a coefficient of -0.0193 (t=-14.65). In the second specification, both coefficients *High ESG&High ESG* and *High ESG&CONV* remain negative and statistically significant (-0.0137, t=-4.47 and

-0.0195, *t*=-15.70, respectively). These results corroborate our main findings: In terms of portfolio composition, high-ESG mutual funds differ from the market and their conventional peers in general, but also from each other in particular.

- Table 7 -

Second, we re-estimate our model using a subsample including only the pairs of funds that survive the sample period (2013q1 –2018q4). This subsample of "survivors" includes 425,503 unique pairs (out of 1,965,175 in the original sample). The results are shown in columns (1) and (2) of Table 7. In the first specification, the *High ESG* estimated coefficient is still highly statistically significant (-1.4734, *t*=-15.60). In the second specification, both *High ESG&High ESG* and *High ESG&CONV* remain negative and significant, with coefficients of -1.0992 (*t*=5.69) and -1.4943 (*t*=-16.46), respectively. Again, these findings confirm the main results of our baseline model runs—columns (1) and (2) of Table 7.

- Table 8 -

Finally, we examine whether our findings are sensitive to the two fund categories: "high-ESG" versus "conventional." In the main model, high-ESG mutual funds are defined as those in the top 10 % oof the distribution of sustainability scores. In Panels A and B of Table 8, we replicate this model with alternative thresholds, 5% and 15%, respectively. In the first columns of Panels A and B, we observe that high-ESG funds differ from the market, regardless of the threshold used to define the high-ESG group. In column (2) of Panel A, we find that the coefficients of both *High ESG&High ESG* and *High ESG&CONV* are negative and statistically significant if we tighten the criteria applied to identify high-ESG mutual funds. These results support our main findings. In column (2) of Panel B, it appears that there is no longer any significant difference between the pairwise similarity of two high-ESGs and two conventional funds if we consider a broader definition of high-ESG funds (-0.1178, *t*=-0.56). Nonetheless, the portfolios of a high-ESG fund and a conventional fund are still less similar than those of two conventional funds (-1.0649, *t*=16.33).

4.2 Financial performance

To test the validity of our results concerning financial performance, we estimate the four specifications in Table 4—Equation 3—with alternative settings. Our robustness checks include using the five-factor alpha to capture the fund performance, an alternative index to assess climate change risk and different thresholds to classify "high-ESG" versus "conventional" funds, as well as estimating our model for a subsample that only includes funds that survive the sample period.

- Table 9 -

In the first step, we use an alternative metric of financial performance. Instead of the four-factor alpha (Carhart, 1997) used previously, we re-estimate the four specifications of Table 4 with the five-factor alpha (Fama and French, 2015) to capture mutual fund performance, like Joliet and Titova (2018).[38] The five-factor model (Fama and French, 2015) captures other features than the four-factor model (Carhart, 1997). In particular, it includes two "quality" factors: (i) the profitability factor and (ii) the investment factor.[39] The rational behind the profitability factor is that more profitable firms should generate returns, while the investment factor captures the amount of reinvested earnings, which should increase returns. Results of these specifications are displayed in Table 9 and confirm our main findings. Notably, in the first column, the coefficient estimate of $HighESG$ confirms that high-ESG funds perform weakly as compared to their conventional peers when the risk-adjusted returns are captured by the five-factor alpha (-0.1183, t=-3.79). Contrary to the main corresponding specification, the level of portfolio distinctiveness negatively and significantly affects the financial performance of conventional funds (-0.0128, t=-3.19). Nevertheless, consistent with

[38] We estimate the five-factor alpha (Fama and French, 2015), with rolling windows of 24 months moving by one quarter: $r_{i,t} - r_t^f = \alpha + \beta_{MKT}(r_t^m - r_t^f) + \beta_{SMB} r_t^{SMB} + \beta_{HML} r_t^{HML} + \beta_{CMA} r_t^{CMA} + \beta_{RMW} r_t^{RMW} + \epsilon_{i,t}$. r^{CMA} denotes the difference in returns of portfolios of stocks of low and high investment firms (i.e., conservative and aggressive, respectively) and r^{RMW} refers to the difference in returns of portfolios of high and low operating profitability stocks. Other variables are defined in Section 2 (Subsections 2.1 to 2.4). The estimated four-factor and five-factor alphas are positively correlated (ρ=0.90).

[39] Nevertheless, the five-factor model (Fama and French, 2015) does not nest the four-factor model (Carhart, 1997) as it excludes the momentum factor, which has been proved to be important in empirical analysis. Recent research contributions have discussed the advantages and disadvantages of the different factor models (e.g., Blitz, 2016; Maiti, 2020). On this basis, and since the four-factor model remains standard in the literature (e.g., El Ghoul and Karoui, 2017; Price and Sun, 2017), we use the four-factor model in our baseline specification and we present the five-factor alpha analysis as a robustness test.

our main findings, this negative effect is stronger for high-ESG funds (-0.0369, t=-3.57). In the third column, the estimated coefficients confirm that climate risk reduces the performance of conventional funds (-0.0117, t=-9.66), while high-ESGs provide a better hedge against this type of risk (0.0212, t=5.02). Finally, the results in the last column confirm that high-ESG funds following more unique investment strategies are better hedge against climate risk (0.00638, t=5.73).

- Table 10 -

In the second step, we use an alternative climate risk metric—the Wall Street Journal (WSJ) index—to test how sensitive the results are to such a change. Similar to the CHNEG index, the WSJ index is based on the analysis of news articles and was developed by Engle et al. (2020). While the CHNEG index focuses on negative news about climate change from various media sources, the WSJ index captures general attention to the climate issue in the Wall Street Journal.[40] The time series of the CHNEG index is available until 2018q2, whereas the WSJ index time series ends four quarters earlier. Table 10gathers the results of the last two specifications—columns (3) and (4)—in Table 4 , estimated by using the WSJ index to capture climate risk.[41] The results obtained with the WSJ index are less clear-cut than those of the main specifications. In the first column, they confirm that an increase in climate risk worsens the future performance of conventional funds (-0.0020, t=-5.36). The coefficient of the interaction term between the dummy and the climate risk index is positive, as in the main specification, but not statistically significant at the 10% level (0.0024, t=1.57). Therefore, the ability of high-ESG funds to hedge against climate risk is less clear-cut if we capture climate risk through an index that does not distinguish between positive and negative climate-related news.

- Table 11 -

In the next step, we re-estimate the four specifications in Table 4 for a subsample including only mutual funds that survive the 2013q1–2018q2 sample period. This subsample of "sur-

[40]See Engle et al. (2020) for more details on the WSJ index. The CHNEG and WSJ indices are positively correlated (ρ=0.4574)

[41]We do not re-estimate the first two specifications—columns (1) and (2)—in Table 4 since they do not include the climate risk variable.

vivors" includes 923 mutual funds. The results of these specifications are presented in Table 11 and are fully consistent with our main findings. In particular, in column (1), the estimated coefficient of the dummy variable $High\ ESG$ confirms that high-ESG funds underperform their conventional counterparts (-0.0944, t=-2.83). In column (2), the results confirm that the level of portfolio distinctiveness does not significantly affect the future performance of conventional funds (-0.0013, t=-0.31), while it lowers the performance of high-ESG funds (-0.0351, t=-3.25). In column (3), the estimates show that climate risk reduces the performance of conventional funds (-0.0084, t=-7.13), while high-ESGs provide a better hedge against this type of risk (0.00107, t=2.15). Finally, the results in the last column confirm that high-ESG funds following more unique investment strategies are a better hedge against climate risk (0.0063, t=4.32).

- Table 12 -

In the final step, we change the threshold applied to identify "high-ESG" mutual funds. In our main specifications, we labeled "high-ESG" those mutual funds whose sustainability score was in the upper 10% of the distribution. Panels A and B of Table 12 show the results of the four specifications in Table 4 if we use alternative thresholds of 5% and 15%, respectively. The estimates in the first columns of Panels A and B suggest that the weak performance of high-ESG funds is amplified if we tighten the criteria used to identify these funds. Indeed, we find that the weak performance of high-ESG funds is statistically significant if we tighten the threshold to 5% (-0.1091, t=-2.81), but not if we relax it to 15% (-0.0353, t=-1.54). Consistent with our findings, the results in the second columns of Panels A and B confirm that the performance of high-ESG funds is negatively affected by the level of portfolio distinctiveness if we raise/lower the threshold (-0.0207, t=-1.65 and -0.0139, t=-2.01, respectively). In the third columns of Panels A and B, in line with the corresponding main specification, it appears that climate risk has a negative impact on the performance of conventional funds (-0.0091, t=-9.01 and -0.0096, t=-9.01, respectively), and that high-ESG funds provide a better hedge against this type of risk (0.0110, t=1.69 and 0.0075, t=2.36, respectively). Finally, the estimated coefficients in the last columns of Panels A and B of Table 12 indicate that high-ESG funds with a unique investment strategy provide a better hedge against climate risk (0.0076, t=4.35 and 0.0038, t=4.67, respectively).

4.3 Flows

To validate our findings on fund flows, we estimate the four specifications in Table 5—Equation 4—with alternative settings. These robustness tests are similar to those we perform for financial performance, that is, we use an alternative index to assess climate change risk and different thresholds to classify "high-ESG" versus "conventional" funds, as well as estimating our model for a subsample that only includes funds that survive the sample period.

- Table 13 -

First, we estimate the third and fourth specifications—columns (3) and (4)—in Table 5 using the WSJ index as a climate risk metric.[42] Table 13 shows the results of these specifications. The estimates in column (1) are in line with those in the corresponding main specification. Indeed, they provide evidence suggesting that fund flows increase when climate risk increases (0.0121, t=2.33) and that this effect does not differ significantly between high-ESGs and conventional funds (0.0017, t=0.11). A one-unit standard deviation increase in the WSJ index increases future flows of conventional funds by 0.1497 (0.0118*12.6850), versus 0.1519 for one standard deviation increase in the CHNEG index. In the second column, the results confirm that the positive impact of climate risk on conventional fund flows is smaller for funds implementing more unique investment strategies (-0.0027, t=-2.19) and that this mitigating effect does not differ significantly for high-ESG funds (-0.0026, t=-0.75).

- Table 14 -

Second, we estimate the four specifications in Table 5 for a subsample that only includes mutual funds that survive the 2013q1–2018q2 sample period. The results of these specifications are presented in Table 14 and provide evidence supporting our main findings. In the first column of this table, the coefficient of the dummy variable $High\ ESG$ iis not statistically significant (-0.1936, t=-0.74). As in the main specification, the results provide no evidence

[42]We do not re-estimate the first two specifications—columns (1) and (2)—in Table 5 since they do not include the climate risk variable.

that high-ESGs and conventional funds differ in terms of the capital flows they attract if we perform our estimation on a restricted sample. In column (2), the estimates confirm that implementing a more unique investment strategy does not attract more capital flows for either conventional (-0.0202, t=-0.42) or high-ESG funds (-0.0385, t=-0.58). Compared to the corresponding main specification, the relationship between fund flows and climate risk is less clear-cut. Even though the estimate remains positive (0.0178, t=1.28), we find in column (3) that it is no longer statistically significant at the 10% level. Consistent with our previous findings, the results provide no evidence of flow reallocation to high-ESG funds (-0.0087, t=-0.30). Finally, the results in the last column confirm that least distinctive funds receive more flows when climate risk increases (0.4941, t=1.81) and that this effect does not differ significantly for high-ESG funds (0.2015, t=0.29). In addition, they indicate that this effect is weakened as the level of portfolio distinctiveness increases (-0.0053, t=-1.73) and that this mitigating effect does not differ significantly for high-ESG funds (-0.0023, t=-0.30).

- Table 15 -

Last, we use alternative thresholds to identify "high-ESG" mutual funds. Panels A and B of Table 15 show the results of the four specifications in Table 5 using alternative thresholds of 5% and 15%, respectively. These results corroborate our main findings. In particular, in the first columns of Panels A and B, the estimated coefficients of $High\,ESG$ are not statistically significant (-0.1732, t=-0.51 and 0.1775, t=0.86, respectively). Moreover, the results in the second columns of Panels A and B confirm that implementing a more unique investment strategy does not attract more capital flows for either conventional (0.0065, t=0.17 and 0.0063, t=0.16, respectively) or high-ESG funds (-0.0862, t=-1.03 and -0.0405, t=-0.7734, respectively). In addition, in the third columns of Panels A and B, we find that conventional funds attract more flows when climate risk increases (0.0227, t=1.90 and 0.0233, t=1.87, respectively). Our results also confirm that this effect is not different for high-ESG funds (0.0044, t=0.11 and 0.0013, t=0.05, respectively). Finally, the estimates in the last columns of Panels A and B in Table 15 corroborate that the positive impact of climate risk on conventional fund flows is lower for funds implementing more unique investment strategies (-0.0071, t=-2.08 and -0.0064, t=-2.35, respectively). As in the main specification, our results provide no evidence that this effect differs for high-ESG funds (-0.0012, t=-0.30 and -0.0057, t=-0.96, respectively).

5 Conclusion

Investment funds marketed as “sustainable” or “ESG” have multiplied in recent years and are attracting increasing attention of various stakeholders in the financial industry, including investors, regulators, and policymakers. Whether such funds actually are any different from regular actors is still a matter of debate, as illustrated by serious, widespread concerns about greenwashing (e.g., Candelon et al., 2021; El Ghoul and Karoui, 2021; Lyon and Maxwell, 2011; Marquis et al., 2016). Our paper contributes to this debate by shedding light on the difference(s) of ESG funds in terms of investment strategies, the returns they offer to their investors, and the capital flows they attract. Using a panel data set of 2,042 U.S. equity mutual funds, we empirically investigated this issue over the period 2013q1–2018q4 and showed how it evolved over time and in response to climate risk.

In terms of investment strategies, our findings suggest that the portfolio compositions of high-ESG funds differ from those of their conventional peers and, more surprisingly, from each other. Over time, however, high-ESG and conventional groups become increasingly similar, while high-ESG portfolios become more homogeneous. Regarding financial performance, our results indicate that, on average, high-ESG funds perform weakly compared to their conventional peers. Nevertheless, they are more resilient to climate risk, erasing the gap in financial performance between the two groups when climate risk increases. Finally, we provide evidence that climate risk increases capital flows, especially into mutual funds with less distinctive investment strategies. However, we cannot find any difference in capital flows between high-ESGs and conventional funds.

While these findings might contribute to the debate on the actual specificity of ESG mutual funds and provide useful information on this topic to various actors in the financial industry, our study is not immune from limitations and could be extended in various directions.

Notably, another avenue for future work would be to verify the implications of our results on portfolio similarity, as measured by portfolio overlap, on market stability. In particular, we show that high-ESG portfolio compositions differ from those of other funds in the market, suggesting that high-ESG mutual funds might help mitigate systemic risks stemming from indirect exposure to the same financial assets, although this stabilization property tends to erode. Future research could empirically test for systemic fragility resulting from portfolio similarity and quantify its economic importance using a shock propagation model (e.g., Cerqueti et al., 2020; Delpini et al., 2019; Lavin et al., 2019). An alternative strategy to identify the systemic risk component arising from portfolio overlap among high-ESG mutual funds and between them and their conventional peers could be to assess excess comovement—i.e., correlation of returns—of stocks held by common mutual fund owners as done in Anton and Polk (2014).

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Tables

Table 1: Summary statistics

	Mean	Med	Sd	Min	Max
# funds per period	1482.83	1336.00	201.07	1276.00	1781.00
Distinctiveness	90.89	89.99	1.48	89.21	92.83
Sustainability score	45.91	46.47	1.87	43.23	48.41
TNA (bn $)	1.77	1.81	0.13	1.48	1.97
Age (years)	17.76	17.68	0.84	16.58	19.72
Flows (% TNA)	-0.55	-0.65	1.41	-3.50	1.63
Flows vol. (%)	3.39	3.33	0.39	2.87	4.21
NER (%)	1.00	1.00	0.01	0.98	1.03
Turnover (%)	14.52	14.33	0.55	13.91	15.78
Net return (%)	2.55	4.27	5.30	-15.52	10.40
Net return vol. (%)	3.47	3.38	0.55	2.71	4.60
# holdings	116.56	110.04	10.13	105.44	129.44
4F alpha	-0.33	-0.36	0.20	-0.66	0.08
R^2 (%)	89.18	89.50	2.51	83.45	93.82
Avg manager tenure (years)	8.82	8.83	0.45	8.17	9.80

Table 1 reports the time-series average of cross-sectional summary statistics for the main variables in our sample for the 2013q1–2018q4 period. These variables are: the number of funds per period, the average portfolio distinctiveness, the sustainability score, the TNA (in bn USD), the age (in years), flows (in % TNA) and volatility computed over the previous 24 months, the NER (in %), turnover (in %), the net return (in %) and its volatility computed over the previous 24 months (in %), the number of holdings, the net four-factor alpha (Carhart, 1997) over the quarter and its associated R^2 (in %), and the average manager tenure (in years).

Table 2: High-ESG versus conventional mutual funds

	High-ESG	CONV	High-ESG - CONV	t-stat
Panel A: Fund-level				
Distinctiveness	91.10	90.76	0.34	0.96
Sustainability score	49.90	45.56	4.34	9.11
TNA (bn $)	2.28	1.75	0.52	6.59
Age (years)	17.65	17.88	-0.24	-0.57
Flows (% TNA)	-0.46	-0.57	0.12	0.24
Flows vol. (%)	3.00	3.42	-0.43	-3.01
NER (%)	0.99	0.99	-0.01	-0.54
Turnover (/‰)	10.82	14.86	-4.04	-16.40
Net return (%)	2.24	2.59	-0.35	-0.25
Net return vol. (%)	3.27	3.47	-0.21	-1.29
Nb holdings	65.94	120.69	-54.75	-25.02
4F alpha	-0.22	-0.35	0.13	1.59
R^2 (%)	82.32	89.97	-7.65	-7.45
Avg manager tenure (years)	9.12	8.81	0.32	1.73
Panel B: Pair-level				
Distinctiveness with High-ESG	87.97	91.41	-3.44	-12.01
Distinctiveness with CONV	91.41	90.81	0.59	1.51

Table 2 reports the average level of our main variables relatively to their group (High-ESG vs Conventional). These variables are defined as in Table 1. At each quarter, we label the funds awarded the highest sustainability score (top 10%) "High-ESG" and the rest "Conventional," and we aggregate the fund's variables for each group. Aggregated values for the High-ESG and Conventional groups are displayed in the first and second columns, respectively. The third column reports the difference in means between the High-ESG and Conventional groups for each variable, while the fourth column displays the t-statistics for those differences.

Table 3: Pairwise similarity

	Dependent variable: $Pairwise\ Similarity_{ij,t}$ (1)	(2)
$High\ ESG_t$	-1.2346***	
	(-14.6373)	
$High\ ESG\&High\ ESG_t$		-0.5324**
		(-2.4610)
$High\ ESG\&CONV_t$		-1.2683***
		(-16.0900)
Constant	22.9042***	20.9902***
	(10.3915)	(9.3861)
Controls	yes	yes
Style FE	yes	yes
Same style FE	yes	yes
Observations	26,832,696	26,832,696
R-squared	0.4817	0.4818
Nb of groups	24	24

Table 3 reports the Fama and MacBeth (1973) estimates of quarterly cross-sectional regressions (2013q1–2018q4) of the pair of funds' similarity (*Pairwise Similarity*) on control variables and sustainability metrics. *High ESG*, *High ESG*&*High ESG*, and *High ESG*&*CONV* are three dummy variables that take the value of one if at least one fund in the pair is high-ESG, both funds in the pair are high-ESG, and only one fund in the pair is high-ESG, respectively. Controls include the normalized product and the absolute difference of the following variables: the number of assets composing a portfolio (*Holdings*), the natural logarithm of a fund's size ($ln(TNA)$) as well as its squared value ($ln(TNA)^2$), fund flows (*Flows*), turnover (*Turnover*), age (*Age*), net expense ratio (*NER*), average manager tenure (*Tenure*), net return (*Return*) and volatility of the latter (*Volatility*). We also include two sets of dummy variables that control for the investment style, represented by the Morningstar Category. The dummies (one variable for each style) of the first set take the value of one if only one fund in the pair belongs to this style, while the dummies of the second set take the value of one if both funds in the pair belong to this style. All independent variables, excluding dummy variables, are normalized to have unit standard deviation. We calculate Newey and West (1987) standard errors (one lag) of the Fama and MacBeth (1973) estimates and we report the associated t-statistics in parentheses (*** p<0.01, ** p<0.05, * p<0.1). The full version of Table 3 can be found in Appendix A.

Table 4: Mutual fund performance

	Dependent variable: $\hat{\alpha}_t$			
	(1)	(2)	(3)	(4)
$High\ ESG_{t-1}$	-0.0675**	1.6562**	-0.2172***	10.4355***
	(-2.3918)	(2.0772)	(-2.6694)	(4.6761)
$Distinctiveness_{t-1}$		-0.0053		-0.0204***
		(-1.4664)		(-3.5285)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.0189**		-0.1170***
		(-2.1298)		(-4.6750)
$CHNEG_{t-1}$			-0.0094***	-0.0800***
			(-9.0602)	(-3.7893)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0085**	-0.4704***
			(2.0589)	(-4.5479)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0008***
				(3.3304)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0053***
				(4.5238)
$ln(Holdings)_{t-1}$	0.0258*	0.0180	0.0258*	0.0179
	(1.9399)	(1.3050)	(1.9532)	(1.3014)
$Flow_{t-1}$	0.0174***	0.0173***	0.0174***	0.0173***
	(20.6997)	(20.7131)	(20.6763)	(20.6083)
$Vol.\ flow_{t-1}$	-0.0036***	-0.0037***	-0.0034***	-0.0035***
	(-2.8577)	(-2.9206)	(-2.7122)	(-2.7807)
$ln(Age)_{t-1}$	-0.0182	-0.0210	-0.0191	-0.0215
	(-1.3061)	(-1.4926)	(-1.3762)	(-1.5378)
$ln(TNA)_{t-1}$	0.0378***	0.0375***	0.0384***	0.0377***
	(6.3795)	(6.3013)	(6.5046)	(6.3787)
NER_{t-1}	-0.2916***	-0.2896***	-0.2909***	-0.2874***
	(-8.5588)	(-8.4856)	(-8.5472)	(-8.4311)
R^2_{t-1}	-0.0118***	-0.0122***	-0.0116***	-0.0120***
	(-6.5700)	(-6.6803)	(-6.7152)	(-6.8265)
$Turnover_{t-1}$	-0.0047***	-0.0047***	-0.0047***	-0.0047***
	(-5.0135)	(-5.0212)	(-5.0408)	(-5.0473)
$Vol.\ return_{t-1}$	-0.3841***	-0.3785***	-0.3770***	-0.3717***
	(-17.8970)	(-17.3295)	(-23.2550)	(-22.4046)
$SP500_{t-1}$			-0.0007***	-0.0007***
			(-20.8972)	(-19.3315)
Constant	2.3901***	2.9244***	4.1114***	5.9251***
	(13.8737)	(7.2833)	(20.3706)	(10.2249)
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,281	30,281	30,281	30,281
R-squared	0.2614	0.2622	0.2516	0.2555

Table 4 reports the results of the panel regression (2013q1–2018q2) of the four-factor risk-adjusted performance ($\hat{\alpha}$) on style (S) and time (Q) fixed effects and the following lagged variables: a dummy that takes the value of 1 if the fund is in the top 10% of the sustainability score distribution ($High\ ESG$), flows ($Flows$), returns volatility over the previous 24 months ($Vol.\ return$), flows volatility over the previous 24 months ($Vol.\ flows$), natural logarithm of the size ($ln(TNA)$), natural logarithm of the number of assets in portfolio ($ln(Holdings)$), R^2 of the 4-factor regression (R^2), annual net expense ratio (NER), turnover ratio ($Turnover$), natural logarithm of fund age ($ln(Age)$). With respect to the first specification, column (2) includes portfolio distinctiveness in the previous period ($Distinctiveness$) as well as its interaction with the $High\,ESG$ dummy as regressors. Column (3) includes the same regressors as in the first one specification?, adds the CHNEG index ($CHNEG$) as well as its interaction with the $High\,ESG$ dummy, the quarterly S&P 500 index ($SP500$), and excludes time fixed effects. With respect to the first specification, column (4) includes $Distinctiveness$ and $CHNEG$, both interacted with the $HighESG$ dummy and with each other, as well as the triple interaction between the $HighESG$ dummy, $Distinctiveness$ and $CHNEG$, and the quarterly S&P 500 index, and excludes time fixed effects. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: Mutual fund flows

	Dependent variable: $Flows_t$			
	(1)	(2)	(3)	(4)
$High\ ESG_{t-1}$	-0.0536	6.9501	-0.1261	9.6925
	(-0.2253)	(1.3139)	(-0.2294)	(0.7089)
$Distinctiveness_{t-1}$		0.0093		0.1468**
		(0.2355)		(2.4615)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.0772		-0.1073
		(-1.3250)		(-0.7111)
$CHNEG_{t-1}$			0.0226*	0.6785***
			(1.8403)	(2.8667)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0043	-0.1791
			(0.1479)	(-0.2836)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0073***
				(-2.7535)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0020
				(0.2816)
$ln(Holdings)_{t-1}$	0.1855	0.1929	0.2314	0.2423*
	(1.3190)	(1.3535)	(1.6356)	(1.6934)
$\hat{\alpha}_{t-1}$	2.8168***	2.8163***	2.7256***	2.7394***
	(20.8336)	(20.8220)	(20.1717)	(20.2201)
$Vol.\ flow_{t-1}$	0.1315***	0.1313***	0.1350***	0.1349***
	(6.2013)	(6.1820)	(6.3514)	(6.3305)
$ln(Age)_{t-1}$	-1.4794***	-1.4808***	-1.4696***	-1.4692***
	(-10.0645)	(-9.9663)	(-9.9511)	(-9.8428)
$ln(TNA)_{t-1}$	-0.3322***	-0.3308***	-0.3309***	-0.3279***
	(-5.5281)	(-5.4873)	(-5.4959)	(-5.4360)
NER_{t-1}	-0.5396*	-0.5444*	-0.5384*	-0.5487*
	(-1.7811)	(-1.7893)	(-1.7704)	(-1.7957)
R^2_{t-1}	-0.0001	0.0002	-0.0147	-0.0144
	(-0.0083)	(0.0136)	(-1.2786)	(-1.2242)
$Turnover_{t-1}$	-0.0255***	-0.0253***	-0.0248***	-0.0248***
	(-2.8933)	(-2.8721)	(-2.8042)	(-2.8089)
$Vol.\ ret_{t-1}$	0.6498***	0.6451***	0.3596***	0.3634***
	(3.7060)	(3.5879)	(2.6969)	(2.6435)
$SP500_{t-1}$			-0.0004	-0.0005
			(-1.1192)	(-1.4029)
Constant	1.1260	0.2537	3.5012**	-9.5859*
	(0.7761)	(0.0621)	(2.0201)	(-1.6706)
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,283	30,283	30,283	30,283
R-squared	0.1039	0.1039	0.0945	0.0950

Table 5 reports the results of the panel regression (2013q1–2018q2) of fund flows ($Flows$) on style (S) and time (Q) fixed effects and the following lagged variables: a dummy that takes the value of 1 if the fund is in the top 10% of the sustainability score distribution ($High\ ESG$), estimated four-factor alpha ($\hat{\alpha}$), returns volatility over the previous 24 months ($Vol.\ return$), flows volatility over the previous 24 months ($Vol.\ flows$), natural logarithm of the size ($ln(TNA)$), natural logarithm of the number of assets in portfolio ($ln(Holdings)$), R^2 of the 4-factor regression (R^2), annual net expense ratio (NER), turnover ratio ($Turnover$), natural logarithm of fund age ($ln(Age)$). With respect to the first specification, column (2) includes portfolio distinctiveness in the previous period ($Distinctiveness$) as well as its interaction with the $High\ ESG$ dummy as regressors. Column (3) includes the same regressors as in the first one specification?, adds the CHNEG index ($CHNEG$) as well as its interaction with the $High\ ESG$ dummy, the quarterly S&P 500 index ($SP500$), and excludes time fixed effects. With respect to the first specification, column (4) includes $Distinctiveness$ and $CHNEG$, both interacted with the $High\ ESG$ dummy and with each other, as well as the triple interaction between the $High\ ESG$ dummy, $Distinctiveness$ and $CHNEG$, and the quarterly S&P 500 index, and excludes time fixed effects. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: Pairwise similarity - Alternative definition of similarity

	Dependent variable: $Pairwise\ Similarity_{alt_{ij,t}}$ (1)	(2)
$HighESG_t$	-0.0193***	
	(-14.6477)	
$HighESG\&HighESG_t$		-0.0137***
		(-4.4677)
$HighESG\&CONV_t$		-0.0195***
		(-15.7010)
Controls	yes	yes
Style FE	yes	yes
Same style FE	yes	yes
Observations	26,832,696	26,832,696
R-squared	0.5159	0.5159
Nb of groups	24	24

Table 6 reports an alternative setting for the specifications presented in Table 3; here, the similarity metric is computed based on the Euclidean distance. All independent variables, excluding dummy variables, are normalized to have unit standard deviation. We calculate Newey and West (1987) standard errors (one lag) of the Fama and MacBeth (1973) estimates and we report the associated t-statistics in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 7: Pairwise similarity - Survivors

	Dependent variable: $Pairwise\ Similarity_{ij,t}$ (1)	(2)
$High\ ESG_t$	-1.4734***	
	(-15.6011)	
$High\ ESG\&High\ ESG_t$		-1.0992***
		(-5.6879)
$High\ ESG\&CONV_t$		-1.4943***
		(-16.4623)
Controls	yes	yes
Style FE	yes	yes
Same style FE	yes	yes
Observations	10,212,072	10,212,072
R-squared	0.5101	0.5102
Nb of groups	24	24

Table 7 reports the same cross-sectional regressions (2013q1–2018q4) as those displayed in Table 3 estimated on a sub-sample of pair of funds that survive the sample from 2013q1 to 2018q4. All independent variables, excluding dummy variables are normalized to have unit standard deviation. We calculate Newey and West (1987) standard errors (one lag) of the Fama and MacBeth (1973) estimates and we report the associated t-statistics in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 8: Pairwise similarity - Alternative high-ESG definition

	Dependent variable: $Pairwise\ Similarity_{ij,t}$ (1)	(2)
	Panel A - Top 5%	
$High\ ESG_t$	-1.5394***	
	(-16.0510)	
$High\ ESG\&High\ ESG_t$		-0.7796***
		(-4.1492)
$High\ ESG\&CONV_t$		-1.5577***
		(-16.4553)
Controls	yes	yes
Style FE	yes	yes
Same style FE	yes	yes
Observations	26,832,696	26,832,696
R-squared	0.4815	0.4815
Nb of groups	24	24
	Panel B - Top 15%	
$High\ ESG_t$	-1.0038***	
	(-13.7784)	
$High\ ESG\&High\ ESG_t$		-0.1178
		(-0.5591)
$High\ ESG\&CONV_t$		-1.0649***
		(-16.3301)
Controls	yes	yes
Style FE	yes	yes
Same style FE	yes	yes
Observations	26,832,696	26,832,696
R-squared	0.4812	0.4816
Nb of groups	24	24

Panels A and B of Table 8 report alternative settings for specifications presented in Table 3; here, high-ESG funds are in the top 5% and 15% of the sustainability score at each quarter, respectively. All independent variables, excluding dummy variables are normalized to have unit standard deviation. We calculate Newey and West (1987) standard errors (one lag) of the Fama and MacBeth (1973) estimates and we report the associated t-statistics in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: Mutual fund performance - 5-factor alpha

	Dependent variable: $\hat{\alpha}5F_t$			
	(1)	(2)	(3)	(4)
$High\ ESG_{t-1}$	-0.1183***	3.2406***	-0.4891***	13.9291***
	(-3.7878)	(3.4977)	(-5.8193)	(6.1023)
$Distinctiveness_{t-1}$		-0.0128***		-0.0241***
		(-3.1895)		(-3.5167)
$High\ ESG * Distinctiveness_{t-1}$		-0.0369***		-0.1582***
		(-3.5655)		(-6.1893)
$CHNEG_{t-1}$			-0.0117***	-0.0589**
			(-9.6568)	(-2.3331)
$High\ ESG * CHNEG_{t-1}$			0.0212***	-0.5969***
			(5.0237)	(-5.6581)
$Distinctiveness_{t-1} * High\ ESG_{t-1}$				0.0005*
				(1.8635)
$High\ ESG * Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0068***
				(5.7272)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,281	30,281	30,281	30,281
R-squared	0.2082	0.2113	0.2020	0.2083

Table 9 reports results for the last two specifications—columns (3) and (4)—in Table 4 estimated using the five-factor alpha (Fama and French, 2015) as dependent variable. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 10: Mutual fund performance - Alternative measure of climate risk

	Dependent variable: $\hat{\alpha}_t$	
	(1)	(2)
$High\ ESG_{t-1}$	-0.2103**	12.3841***
	(-1.9717)	(4.8009)
$Distinctiveness_{t-1}$		-0.0287***
		(-3.9369)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.1384***
		(-4.8012)
WSJ_{t-1}	-0.0020***	-0.0361***
	(-5.3566)	(-4.5213)
$High\ ESG_{t-1} * WSJ_{t-1}$	0.0024	-0.1756***
	(1.5694)	(-4.8923)
$Distinctiveness_{t-1} * WSJ_{t-1}$		0.0004***
		(4.1887)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * WSJ_{t-1}$		0.0020***
		(4.8701)
Controls	yes	yes
Style FE	yes	yes
Time FE	no	no
Observations	23,936	23,936
R-squared	0.2949	0.2971

Table 10 reports results for the last two specifications—columns (3) and (4)—in Table 4 estimated using an alternative index of climate change risk: the WSJ index. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 11: Mutual fund performance - Survivors

	Dependent variable: $\hat{\alpha}_t$			
	(1)	(2)	(3)	(4)
$High\ ESG_{t-1}$	-0.0944***	3.0886***	-0.2869***	13.5054***
	(-2.8279)	(3.2019)	(-2.8502)	(4.8252)
$Distinctiveness_{t-1}$		-0.0013		-0.0224***
		(-0.3062)		(-3.1602)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.0351***		-0.1515***
		(-3.2532)		(-4.8220)
$CHNEG_{t-1}$			-0.0084***	-0.1042***
			(-7.1334)	(-4.0728)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0107**	-0.5595***
			(2.1457)	(-4.3536)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0011***
				(3.7203)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0063***
				(4.3239)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	20,213	20,213	20,213	20,213
R-squared	0.2510	0.2530	0.2396	0.2473

Table 11 reports results for the four specifications in Table 4 estimated on a subsample of funds that survive the 2013q1–2018q2 sample period. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 12: Mutual fund performance - Alternative high-ESG definition

	Dependent variable: $\hat{\alpha}_t$			
	(1)	(2)	(3)	(4)
Panel A - Top 5%				
$High\ ESG_{t-1}$	-0.1091***	1.7871	-0.3016**	14.2896***
	(-2.8054)	(1.5685)	(-2.3910)	(4.2900)
$Distinctiveness_{t-1}$		-0.0061*		-0.0239***
		(-1.6988)		(-4.2051)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.0207*		-0.1596***
		(-1.6487)		(-4.2974)
$CHNEG_{t-1}$			-0.0091***	-0.0921***
			(-9.0060)	(-4.3867)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0110*	-0.6860***
			(1.6937)	(-4.3691)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0009***
				(3.9353)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0076***
				(4.3454)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,281	30,281	30,281	30,281
R-squared	0.2617	0.2623	0.2518	0.2554
Panel B - Top 15%				
$High\ ESG_{t-1}$	-0.0353	1.2198**	-0.1673***	7.5339***
	(-1.5365)	(1.9833)	(-2.7203)	(4.8656)
$Distinctiveness_{t-1}$		-0.0052		-0.0187***
		(-1.4119)		(-3.1414)
$High\ ESG * Distinctiveness_{t-1}$		-0.0139**		-0.0850***
		(-2.0062)		(-4.8696)
$CHNEG_{t-1}$			-0.0096***	-0.0741***
			(-9.0142)	(-3.3954)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0075**	-0.3400***
			(2.3611)	(-4.6767)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0007***
				(2.9433)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				0.0038***
				(4.6682)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,281	30,281	30,281	30,281
R-squared	0.2612	0.2619	0.2514	0.2550

Table 12 reports results for the four specifications in Table 4 estimated with alternative definition of the high-ESG group. In Panel A, high-ESG mutual funds are defined as those whose sustainability score is in the top 5% of the distribution. In Panel B, high-ESG mutual funds are defined as those whose sustainability score is in the top 15% of the distribution. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 13: Mutual fund flows - Alternative measure of climate risk

	Dependent variable: $Flows_t$	
	(1)	(2)
$High\ ESG_{t-1}$	-0.1664	-6.7276
	(-0.1621)	(-0.2979)
$Distinctiveness_{t-1}$		0.1715*
		(1.8159)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		0.0738
		(0.2940)
WSJ_{t-1}	0.0121**	0.2373**
	(2.3265)	(2.1561)
$High\ ESG_{t-1} * WSJ_{t-1}$	0.0017	0.2377
	(0.1109)	(0.7569)
$Distinctiveness_{t-1} * WSJ_{t-1}$		-0.0027**
		(-2.1876)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * WSJ_{t-1}$		-0.0026
		(-0.7512)
Controls	yes	yes
Style FE	yes	yes
Time FE	no	no
Observations	23,938	23,938
R-squared	0.1024	0.1063

Table 13 reports results for the last two specifications—columns (3) and (4)—in Table 5 estimated using an alternative index of climate change risk: the WSJ index. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 14: Mutual fund flows - Survivors

	Dependent variable: $Flows_t$			
	(1)	(2)	(3)	(4)
$High\ ESG_{t-1}$	-0.1936	3.3093	-0.0405	-0.6897
	(-0.7416)	(0.5510)	(-0.0697)	(-0.0449)
$Distinctiveness_{t-1}$		-0.0202		0.0849
		(-0.4245)		(1.2274)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.0385		0.0074
		(-0.5798)		(0.0439)
$CHNEG_{t-1}$			0.0178	0.4941*
			(1.2819)	(1.8101)
$High\ ESG_{t-1} * CHNEG_{t-1}$			-0.0087	0.2015
			(-0.2997)	(0.2888)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0053*
				(-1.7345)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0023
				(-0.3018)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	20,213	20,213	20,213	20,213
R-squared	0.0993	0.0994	0.0892	0.0896

Table 14 reports results for the four specifications in Table 5 estimated on a subsample of funds that survive the 2013q1–2018q2 sample period. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 15: Mutual fund flows - Alternative high-ESG definition

	Dependent variable: $Flows_t$			
	(1)	(2)	(3)	(4)
Panel A - Top 5%				
$High\ ESG_{t-1}$	-0.1732	7.7020	-0.2423	4.4316
	(-0.5062)	(0.9788)	(-0.3153)	(0.2312)
$Distinctiveness_{t-1}$		0.0065		0.1413**
		(0.1677)		(2.4350)
$High\ ESG_{t-1} * Distinctiveness_{t-1}$		-0.0862		-0.0508
		(-1.0033)		(-0.2393)
$CHNEG_{t-1}$			0.0227*	0.6641***
			(1.9003)	(2.9233)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0044	0.1133
			(0.1072)	(0.1142)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0071***
				(-2.8034)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0012
				(-0.1114)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,283	30,283	30,283	30,283
R-squared	0.1039	0.1039	0.0945	0.0950
Panel B - Top 15%				
$High\ ESG_{t-1}$	0.1775	3.8237	0.1545	-6.0346
	(0.8555)	(0.8115)	(0.3274)	(-0.5381)
$Distinctiveness_{t-1}$		0.0063		0.1271**
		(0.1570)		(2.0931)
$High\ ESG * Distinctiveness_{t-1}$		-0.0405		0.0692
		(-0.7734)		(0.5555)
$CHNEG_{t-1}$			0.0233*	0.5986**
			(1.8726)	(2.4625)
$High\ ESG_{t-1} * CHNEG_{t-1}$			0.0013	0.5085
			(0.0539)	(0.9623)
$Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0064**
				(-2.3507)
$High\ ESG_{t-1} * Distinctiveness_{t-1} * CHNEG_{t-1}$				-0.0057
				(-0.9624)
Controls	yes	yes	yes	yes
Style FE	yes	yes	yes	yes
Time FE	yes	yes	no	no
Observations	30,283	30,283	30,283	30,283
R-squared	0.1039	0.1039	0.0946	0.0950

Table 15 reports results for the four specifications in Table 5 estimated with alternative definition of the high-ESG group. In Panel A, high-ESG mutual funds are defined as those whose sustainability score is in the top 5% of the distribution. In Panel B, high-ESG mutual funds are defined as those whose sustainability score is in the top 15% of the distribution. All continuous variables are winsorized at the 1% level. Robust t-statistics, clustered at the fund-level, are in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Appendices

A Full version of Table 3

Table 16: Pairwise similarity

	Dependent variable: $Pairwise\ Similarity_{ij,t}$ (1)	(2)
$High\ ESG_t$	-1.2346***	
	(-14.6373)	
$High\ ESG\&High\ ESG_t$		-0.5324**
		(-2.4610)
$High\ ESG\&CONV_t$		-1.2683***
		(-16.0900)
Controls (product)		
$Holdings_t$	1.0543***	1.0541***
	(22.9281)	(22.9079)
$ln(TNA)_t$	-1.8024***	-1.7947***
	(-19.4492)	(-19.4825)
$ln(TNA)^2_t$	2.3901***	2.3830***
	(22.7469)	(22.8069)
Age_t	0.3597***	0.3599***
	(18.7230)	(18.7276)
$Tenure_t$	-0.1594***	-0.1597***
	(-9.2836)	(-9.3012)
$Turnover_t$	0.3034***	0.3039***
	(7.7422)	(7.7593)
$Flow_t$	-0.0053	-0.0053
	(-1.2112)	(-1.2125)
NER_t	-0.3327***	-0.3333***
	(-10.3681)	(-10.3584)
$Return_t$	0.0786	0.0785
	(0.8017)	(0.8009)
$Vol.return_t$	-0.2687**	-0.2674**
	(-2.6645)	(-2.6547)
Controls (absolute difference)		
$Holdings_t$	-0.2309***	-0.2298***
	(-17.0739)	(-16.9532)
$ln(TNA)_t$	-0.0967	-0.0886
	(-0.4597)	(-0.4222)
$ln(TNA)^2_t$	0.1034	0.0948
	(0.5276)	(0.4841)
Age_t	-0.0706***	-0.0707***
	(-7.4258)	(-7.4590)
$Tenure_t$	0.0183	0.0185
	(1.6426)	(1.6514)
$Turnover_t$	-0.1249***	-0.1242***
	(-8.8168)	(-8.7694)
$Flow_t$	-0.0184	-0.0186
	(-1.2238)	(-1.2385)
NER_t	-0.0710***	-0.0705***
	(-4.7806)	(-4.7646)
$Return_t$	-0.9882***	-0.9880***
	(-9.5632)	(-9.5634)
$Vol.return_t$	-0.9173***	-0.9169***
	(-7.4909)	(-7.4893)

Continued on next page

Table 16: *(Continued)* Pairwise similarity

	Dependent variable: $Pairwise\ Similarity_{ij,t}$ (1)	(2)
Constant	22.9042***	20.9902***
	(10.3915)	(9.3861)
Style FE	yes	yes
Same style FE	yes	yes
Observations	26,832,696	26,832,696
R-squared	0.4817	0.4818
Number of groups	24	24

Table 16 reports the Fama and MacBeth (1973) estimates of quarterly cross-sectional regressions (2013q1–2018q4) of the pair of funds' similarity ($Pairwise\ Similarity$) on control variables and sustainability metrics. $HighESG$, $HighESG\&HighESG$, and $High\ ESG\&CONV$ are three dummy variables that take the value of one if at least one fund in the pair is high-ESG, both funds in the pair are high-ESG, and only one fund in the pair is high-ESG, respectively. Controls include the normalized product and the absolute difference of the following variables: the number of assets composing a portfolio ($Holdings$), the natural logarithm of a fund's size ($ln(TNA)$) as well as its squared value ($ln(TNA)^2$), fund flows ($Flows$), turnover ($Turnover$), age (Age), net expense ratio (NER), average manager tenure ($Tenure$), net return ($Return$) and volatility of the latter ($Volatility$). We also include two sets of dummy variables that control for the investment style, represented by the Morningstar Category. The dummies (one variable for each style) of the first set take the value of one if only one fund in the pair belongs to this style, while the dummies of the second set take the value of one if both funds in the pair belong to this style. All independent variables, excluding dummy variables, are normalized to have unit standard deviation. We calculate Newey and West (1987) standard errors (one lag) of the Fama and MacBeth (1973) estimates and we report the associated t-statistics in parentheses (*** p<0.01, ** p<0.05, * p<0.1).