Climate uncertainty and investor learning in sustainable funds.

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Abstract

This paper presents a novel take on the effect of uncertainty on investor learning about managerial skills by examining the fund flow-performance relationship in ESG rated funds in the context of climate uncertainty. Utilizing a large sample of mutual funds domiciled in Australia and New Zealand and recently developed transition and physical climate risk indexes for the Australia-Oceania region, we show that investor learning regarding manager skills is affected by not only the nature of climate uncertainty faced by decision makers, but also the sustainability ratings of the funds under consideration. While the response of fund flows to past performance is found to be stronger for funds with higher sustainability scores, we show that high climate risk dampens investors' ability to process information when it comes to funds with lower sustainability scores, thus hindering their ability to differentiate fund manager skill from luck. Our findings suggest that investor learning could be enhanced by the ESG performance of funds even under high uncertainty. We underscore the informational value captured by ESG ratings from a novel angle, particularly during periods of higher climate uncertainty. Our findings have implications for the managed fund industry and the information asymmetries that may arise between fund managers and investors.

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1. Introduction

The literature on climate finance has picked up steam in recent years with a rapidly increasing number of works showing that climate risk is an important factor in corporate investment (Rodriguez Lopez et al., 2017; Engle et al., 2020) and asset allocation decisions (Krueger et al., 2020, Ceccarelli et al., 2023). Some papers in this growing strand of the literature approach climate risk from the perspective of time-varying disaster risks along the lines of Gourio (2012) and Wachter (2013), among others, and highlight the challenges posed by climate risks on economic growth prospects (e.g. Stern, 2007) and firm profitability (e.g. Pankratz et al., 2019; Addoum et al., 2020). While this line of research emphasizes climate risk which materializes in a physical form such as floods/heat waves or climate chronic hazards, a separate strand of this literature focuses on the transitionary aspects of climate change on the economy and business profitability that are typically prompted by changes in climate-related policies, technological advances and shift in public preferences towards climate friendly investments (Bua et al., 2021, Cepni et al., 2023). Regardless of the channel in which climate risk impacts economic dynamics, a growing number of papers characterize climate risk as a long-run risk factor in financial markets (e.g. Bansal et al., 2017) and document robust evidence that climate risk exposure serves as a systematic driver of returns in equity (e.g. Faccini et al., 2021, Bolton and Kacperczyk, 2021, Bua et al., 2021 and Hsu et al., 2022), bond (e.g. Painter, 2020 and Huynh and Xia, 2021) and real estate markets (e.g. Baldauf et al., 2020, Murfin and Spiegel, 2020 and Bernstein et al., 2019).

This paper presents a novel view on the nexus between climate uncertainty and financial market dynamics by investigating how climate risk affects investor learning regarding managerial skills. Specifically, utilizing a large sample of mutual funds domiciled in Australia and New Zealand and recently developed transition and physical climate risk indexes for the Australia-Oceania region, we examine the effect of climate uncertainty on the fund flow-performance relationship in environmental, social and governance (ESG) rated funds based on Morningstar ratings. Our study has two significant contributions. First, we develop two novel indexes of climate risk for the Australia-Oceania region via textual analysis of an extensive list of news articles from *The Australian* and *The New Zealand Herald* newspapers associated with the region over the period January 2018 through December 2022. Our procedure is able to capture the distinction between physical and transition risks associated with climate change prompted by physical climate events or the regulatory or operational impact of climate risks. To the best of our knowledge, ours is the first in the literature to propose measures of physical and transitional climate risk for the Australia-Oceania region. The second contribution of our study is to extend the burgeoning literature on climate finance to a unique direction by examining how climate uncertainty affects investor learning regarding managerial skills in the managed fund industry. To this end, we examine the relationship between fund flows and past performance via alternative methodologies that incorporate climate risk as a determinant of fund flow performance sensitivities. To enlarge our understanding further, we examine whether the ESG performance of a fund plays a role in how uncertainty impacts investor learning. To the best of our knowledge, this is the first such study that examines investor learning in the climate context via the fund flow performance relationship analysis.

Our main hypothesis is motivated by the well-established evidence in the literature that investment flows in the managed fund industry often serve as an indicator of investor sentiment (e.g., Frazzini and Lamont, 2008; Ben-Rephael et al., 2012) and investors use signals from past performance of funds to infer managerial skills (Huang et al., 2007). Such a learning effect paves the way to a predictive relationship between fund flows and past performance that is well documented in the literature (e.g., Berk and Green, 2004; Franzoni and Schmalz, 2017; Huang et al., 2022). Berk and Green (2004) provide the theoretical underpinnings of the learning effect and argue that the empirical flow-performance relationship reflects Bayesian (rational) investor learning about the skill of mutual fund managers such that past performance provides signals to investors, which in turn creates an informational channel. Later, Huang et al. (2022) further confirm that the flow-performance relationship is consistent with the Bayesian learning process and show that the flow-performance sensitivity of managed funds is weaker for funds with higher return volatility, arguing that volatile past performance provides noisy signals regarding managerial ability, thus hindering the learning process. None of these works, however, has examined investor learning in the context of ESG rated funds although the information reflected by the ESG rating of a fund can be argued to alleviate some of the informational asymmetries that may arise between the fund managers and investors, contributing to the learning process. This is indeed an interesting opening that we explore in our analysis as it adds another dimension to the informational value captured by ESG ratings.

In another strand of literature that deals with investor learning in the context of managed funds, evidence suggests that uncertainty faced by investors plays a significant role in the fund flow-performance relationship, arguing that higher uncertainty hinders investor learning about managerial skills (e.g. Jiang et al., 2021, Ali et al., 2023), thus leading to an inefficient capital allocation by investors.[2] The role of uncertainty is further emphasized by Franzoni and Schmalz (2017) who show that uncertainty regarding the risk loadings on benchmark factors affects investors' capital allocation decisions, thus reducing the flow-performance sensitivity in extreme markets states. Although the previous empirical works on the US mutual fund industry show that investors reward funds in an asymmetric fashion based on their past performance, i.e., they invest in good performers more aggressively than they sell bad performers, (e.g., Sirri and Tufano, 1998; Del Guercio and Tkac, 2002, among others), none of these works has explored the issue in the context of climate uncertainty that has been shown in recent studies to be a significant concern when making investment decisions (Krueger et al., 2020, Ceccarelli et al., 2023).

As mentioned earlier, one of the novelties of our work is that we examine the effect of climate uncertainty on investor learning in the context of ESG performance of managed funds. The literature on the fund flow-performance relationship in the context of sustainable funds is relatively less developed and mostly focuses on the comparison of sustainable funds against their conventional counterparts. For example, Bollen (2007) shows that flows to socially responsible investment (SRI) funds are positively (negatively) related to positive (negative) past performance. Similarly, Renneboog et al. (2011) show that SRI funds are generally less concerned about negative returns relative to non-SRI funds (or conventional funds) based on the flow-performance sensitivity for such funds. The authors further argue that SRI funds care less (more) about the financial (non-financial) attributes of the investment. Against this backdrop, we build on the above literature in three respects. First, we construct two news-based climate uncertainty indexes for the Australia-Oceania region that capture the physical and transitional aspects of climate change. Second, we examine the fund-flow performance relationship for a large sample of mutual funds categorized based on their ESG ratings. This allows us to make inferences on the role of ESG ratings on investor learning regarding manager skills. Finally, we study the effect of our newly

[2] These recent works, thus, add a new perspective to the relationship between stock market dynamics and uncertainty that is shown to drive return and volatility dynamics in financial markets (see Pastor and Veronesi, 2013; Kelly et al., 2016; You et al., 2017; Liu and Zhang, 2015; Ali et al., 2022b; among others).

developed climate risk indices (transition and physical) on the fund flow-performance relationship for funds with high and low ESG ratings, enlarging our understanding of the nexus between climate uncertainty, ESG performance and investor learning.

We find that investor learning regarding manager skills is affected by not only the nature of climate uncertainty faced by decision makers, but also the sustainability ratings of the funds under consideration. The response of fund flows to past performance is found to be particularly stronger for low ESG risk funds, i.e., funds with higher sustainability scores, suggesting that rational investors use past returns as a signal to form their posterior expectations about the ability of a fund manager, more so when a fund enjoys high ESG ratings. In contrast, we find that high transition climate risk dampens the flow-performance relationship, particularly in the case of funds with poor sustainability ratings, implying that investor learning about managerial skills in funds with high ESG risk is significantly hindered by the type of climate uncertainty that is associated with the operational or regulatory changes faced by certain institutions or sectors of the economy. We argue that favourable ESG performance for a fund helps to mitigate information asymmetries between the investors and fund managers, which in turn enhances investor learning regarding fund manager ability based on signals from past performance.

Our findings highlight the informational value captured by ESG ratings on investor learning, particularly when faced with higher climate uncertainty that affects the economy both from the physical and transitionary perspectives. Although the evidence in the literature generally suggests that high uncertainty dampens investors' ability to process information regarding managerial skills, our findings show that the learning process in fact could be enhanced by the ESG performance of funds, even under high uncertainty. While climate uncertainty serves as a significant determinant of fund flows as a standalone factor, particularly for funds that enjoy favourable sustainability ratings, our findings show that high climate risk dampens investors' ability to process information when it comes to funds with poor ESG performance, thus hindering their ability to differentiate fund manager ability from luck. These findings have significant implications for the managed fund industry and the information asymmetries that may arise between fund managers and investors.

The remainder of the paper is organized as follows. Section 2 describes the data and the methodology for constructing climate risk indexes. Section 3 presents the empirical results on the fund flow-performance relationship in ESG rated funds and the role of climate uncertainty. Section 4 discusses the findings from various robustness checks to ensure the robustness of our inferences to alternative model specifications. Finally, Section 5 provides our concluding remarks with suggestions for future research.

2. Data and Methodology

2.1. Data

We employ the survivorship bias-free mutual fund dataset that includes all available open-end equity funds from Morningstar Direct for the universe of funds domiciled in Australia and New Zealand (ANZ). Since Morningstar provides the fund-level sustainability (ESG) ratings data from January 2018, our sample period covers January 2018 through December 2022. Globally, Morningstar launched the Sustainability Ratings over 40,000 mutual funds into a simple rating scale between one and five globes as depicted in Figure A1 in the Appendix. The rating system was designed to provide "a reliable, objective way" to evaluate how investments are meeting environmental, social, and governance challenges wherein funds are classified based on the underlying holdings.[3] In this setting, each holding is assigned a sustainability score based on the research of public documents undertaken by Sustainalytics, an independent Morningstar company that provides ESG ratings and analytics for listed companies. The ratings are based on how a firm scores on ESG issues and at the end of each month, Morningstar takes the weighted average of this measure based on the fund's holdings to form a fund-specific sustainability score. Each fund in a Morningstar category is then ranked based on its sustainability score and this ranking serves as the basis of the Morningstar globe ranking depicted in Figure A1. It must, however, be noted that Morningstar provides ESG ratings for only a subset of the funds from the overall universe of funds because their rating system requires that a large portion of the fund's ESG risk is not left unrated by the corporate or sovereign risk rating frameworks. However, not all funds meet this criterion, therefore within the Morningstar database, a considerable number of funds remain unrated. Since our focus is specifically on the role of ESG ratings on investor learning in the

[3] For details, see http://news.morningstar.com/articlenet/article.aspx?id=745467.

context of climate uncertainty, in our analysis, we use only the funds that meet the Morningstar's ESG rating requirement.[4]

After excluding funds with missing ESG ratings and other information such as returns and total net assets (TNA), our final sample yields an average of 2,724 funds per month across the two countries, among them on average 2,050 are alive (surviving) and 674 are defunct or dead (liquidated/merged), resulting in a total of 59,743 fund-month observations for our analyses. Figure 1 presents the distribution of the mutual funds in the sample across the five sustainability ratings over the period 2018-2022. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). Thus, Morningstar assigns a fund with high (low) ESG risk relative to its Morningstar Global Category as 1 (5) globe. In order to enrich our inferences, we further distinguish between the domestic funds (funds that invest primarily in stocks of the country of domicile) and international funds (funds that invest primarily in stocks of countries different from the country of domicile). To classify the funds based on their international or domestic focus, we use the fund investment category from Morningstar which results in 1,004 (1,720) funds classified as domestic (international), on average. Overall, our final dataset includes a large sample of mutual funds covering two significant markets in the Australia-Oceania region with a total net asset value of $533 billion, representing a sizeable chunk of the mutual fund population and unique set of panel data (when aggregated at the country level) for each month.

Table 2 presents descriptive statistics for the sample of funds used in the multivariate tests. Panel A presents the monthly average each year and Panel B reports the monthly fund statistics across the ESG ratings. We observe in Panel A that the average annual fund flow is consistently negative during the sample period. In Panel B, while the funds in each ESG category experience net outflows, we observe that funds in the high ESG risk category significantly outperform those in the low-risk category, by a 0.34% per month margin, possibly reflecting the compensation investors place on high ESG risk funds. On the other hand, we find no significant difference in fund flows between the high and low risk funds. Table 3 provides further details regarding fund characteristics for the whole sample (Panel A) and low and high ESG risk samples (Panels B and

[4] Complete details of the methodology can be found at : https://www.morningstar.com/content/dam/marketing/shared/research/methodology/744156_Morningstar_Sustainability_Rating_for_Funds_Methodology.pdf

C, respectively). On average, we observe net outflows in all panels, suggesting that ANZ funds had investor outflows during the sample period. While high ESG risk funds outperform low ESG risk funds based on raw returns, the opposite holds when we adjust fund returns for risk based on the four-factor model of Carhart (1997). This could be as more sustainable a fund is, less prone the fund becomes to market wide risks in the long run. This is further supported by the lower return volatility experienced by low ESG risk funds (5.927%) compared to those with high ESG risk (6.391%), along with lower idiosyncratic volatility. Further categorizing the funds based on their domestic and international focus, i.e., whether they primarily invest in domestic or foreign securities, we observe in Table A1 in the Appendix that international funds on average experience outflows to a lesser extent, while these funds outperform their domestic counterparts on a risk-adjusted basis. At the same time, domestic funds are more volatile and smaller in size. Finally, the pairwise correlations presented in Panel F in Table A1 indicate a positive correlation between risk adjusted returns and fund flows, while flows are negatively correlated with fund age, volatility and idiosyncratic volatility.

2.2. Measuring climate risk

To examine the role of climate uncertainty in the fund flow-performance relationship across the ESG rated funds in our sample, we construct novel measures of physical and transition climate risk for the Australia-Oceania region. Following the approach adopted in Bua et al. (2021), we perform a detailed textual analysis of an extensive list of news articles from *The Australian* and *The New Zealand Herald* associated with the region for the 2018–2022 period as these newspapers are a popular source of news for the finance industry to update investment decisions.[5] To this end, we adopt the physical and transition climate risk weighted vocabularies of Bua et al. (2021) which are constructed based on a list of authoritative and scientific texts on climate change published by governmental authorities and other institutions. Specifically, Bua et al. (2021) construct two distinct climate risk vocabularies with each term associated with a term-frequency inverse-document-frequency score as a measure of term-relevance. Next, we employ the cosine-similarity approach, employed by Engle et al. (2020) and Bua et al. (2021), to compare the climate risk vocabularies with the corpus of daily news associated with the Australia-Oceania region and

5 We retain English language news with maximum length of 5,000 words sourced from the Factiva database for *The Australian* (all sources) and *The New Zealand Herald* newspapers with a regional focus on Australia and Oceania. We then apply a one-day novelty filter to remove repetitive news and redundancy in the data.

generate physical and transition concern series representing the percentage of news coverage dedicated to each type of risk. Finally, we estimate an autoregressive model of order 1 (AR1) and use the residuals from the model to construct the Physical Risk Index (PRI) and the Transition Risk Index (TRI) that represent the two aspects of climate risk. To get the monthly TRI and PRI series, we consider the shocks to the averaged-monthly transition and physical concern time series respectively.

Figures 2 and 3 present the time series plots for the climate risk series constructed over the 2018–2022 period. Specifically, the figures show the daily physical and transition media concerns generated by the textual analysis of news articles and a selection of the most relevant PRI and TRI topics (Panel A), the corresponding monthly transition and physical concern time series (Panel B), and the monthly PRI and TRI (Panels C). Table A2 in the Appendix summarises the AR (1) estimates from the monthly concern time series models formulated as

$$Concern_{t,PR} = c_{PR} + \phi_{PR} Concern_{t-1,PR} + PRI_{t,PR} \tag{1a}$$

$$Concern_{t,TR} = c_{TR} + \phi_{TR} Concern_{t-1,TR} + TRI_{t,TR} \tag{1b}$$

where *Concern* is the daily physical and transition media concerns representing the percentage of news coverage dedicated to each type of risk, *c* is the drift parameter, ϕ is the autoregressive coefficient and PRI and TRI are the residuals. Consistent with Bua et al. (2021), both physical risk and transition risk concerns have a positive drift suggesting a rise in the news coverage of these topics over time, with the transition risk coverage being higher and more persistent than that of physical risk ($c_{TR} > c_{PR}$ and $\phi_{TR} > \phi_{PR}$). Further performing the commonality test of Dang et al. (2015), we find that 80.5% of the total information embedded in PRI and TRI is accounted for by individual information, implying that our procedure is able to capture the distinction between physical and transition risks associated with climate concerns.

The visual inspection of Figures 2 and 3 provides several clues regarding some of the notable events that result in spikes in our climate risk index series. For example, examining the transition climate risk series in Figure 2, we observe the largest shock for TRI is recorded on 08/12/2022, following the release of news concerning the use of renewable energies, like wind and solar, and green hydrogen to support the energy transition, as well as talks about the Australian emissions reduction goals along with the discussion on the application of environmental policies, like the Australian Nature Repair Market Regulation. In contrast, the peak for the physical climate risk index in Figure 3 is observed on 20/05/2020, primarily as a result of the discussions on an extreme drought hitting Auckland, New Zealand, highlighting the risks on water scarcity. Other PRI peaks relate to the eruption of the underwater Hunga Tonga, cyclone Cody, and other weather events and consequences of physical hazards. These notable spikes are further identified in Tables A3 and A4 in the Appendix where we provide a summary of the top ten days with the highest physical and transition risk shocks over the period Jan 2018-Dec 2022. We observe that high climate shock days encompass a range of physical and transition risk topics. While the PRI series captures various acute physical risks such as floods, tsunamis, cyclones, extreme weather events and chronic risks like rising sea temperatures, droughts, and sea level rise, it is also able to detect news about climate adaptation calls and adverse impacts on ecosystems, such as a loss of biodiversity. It must be noted that this feature of our physical climate risk index distinguishes it from other physical risk databases that primarily associate physical risks with extreme weather events only.[6] In contrast, we see that transition risk spikes with news on regulations and measures to reduce GHG emissions. This includes the development regarding Australia's effort to meet the climate targets set by the Paris Agreement. Furthermore, news on the costs associated with the transition or advancements in technological innovation and renewable energies to achieve net-zero emissions balance also contribute to high TRI values. Overall, our climate risk series successfully capture various aspects of uncertainty that can be attributed to climate concerns, both from the physical and transitionary or regulatory perspectives.

2.3. Fund flow-performance relationship

To construct the monthly net fund flow series for each fund in the sample, we follow the methodology proposed by Chevalier and Ellison (1997), Sirri and Tufano (1998), Franzoni and Schmalz (2017), among others. Let $TNA_{i,t}$ be the total net assets (in USD) of fund *i* at the end of month *t*. Fund flow for fund *i* in month *t* is then computed as

$$FLOW_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \quad \textbf{(2)}$$

[6] Compared to the European PRI developed by Bua et al. (2021), our Australia-Oceania PRI captures additional types of physical hazards that are more typical of the Australia-Oceania region, such as tsunamis and cyclones.

where and $R_{i,t}$ is the return of fund i in month t. Similarly, following the literature, we measure fund performance using the risk-adjusted returns, computed as the Carhart (1994) four-factor alpha, by estimating $R_{i,c,t} - \beta_i^{mkt} MKT_m + \beta_i^{smb} SMB_m + \beta_i^{hml} HML_m + \beta_i^{mom} MOM_m$ where $R_{i,c,t}$ is the fund's raw return.[7] The model is estimated using a 36-month rolling window regression for each fund and if fewer than 36 monthly return observations are available, we use a 24-month window instead. To calculate the alphas, we adopt a region-based approach to risk adjustment similar to Bekaert et al. (2009) and Ferreira, Keswani, Miguel and Ramos (2012). Motivated by the argument in Hollenstein (2022) that regional factor models capture substantially larger average absolute alphas than local factor models, implying that regional risk factors can appropriately capture the alphas as opposed to country-specific risk factors, we estimate the fund alphas using the risk factors for the Australia-Oceania region, obtained from Ken French's data library based on Fama and French (2012).[8]

The benchmark model to test the fund flow-performance relationship is formulated as

$$FLOW_{i,t} = b_1 PERF_{i,t-1} + b_2 PERF\_Squared_{i,t-1} + CONTROLS_{i,t} + u_i + v_t + e_{i,t} \qquad \textbf{(3)}$$

where $FLOW_{i,t}$ is the new money growth for fund i in month t and fund performance, $PERF$, is measured by the four-factor (CH-4) alphas as explained earlier. Note that we include in the model the fund and time fixed effects captured by u_i and v_t, respectively, to ensure the results are not driven by fund characteristics or time trends; the standard errors are also double clustered by fund and time. Given that our sample includes mutual funds from Australia and New Zealand, we also include a country dummy in the model to account for country fixed effects. However, for the simplicity of exposition, we exclude the country subscript in our formulas. This model tests the effect of past performance on subsequent fund flows where a positive and significant b_1 value indicates that investors use past performance as a signal for future performance, thus leading to a positive (negative) effect on subsequent flows as a result of positive (negative) performance. Finally, the model also includes the square of the performance term ($PERF\_Squared_{i,t-1}$) to account for potential non-linearities in the relationship between past performance and flows.

2.4. The effect of climate uncertainty on fund flow performance sensitivity

[7] It must be noted that the flow-performance relationship remains largely consistent when we use market-adjusted fund returns and CAPM-alphas (additional results are available upon request).

[8] Ken French's data library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#International.

To test the fund flow-performance relationship in the context of climate risk, we augment the benchmark model in Equation 3 to account for the effect of climate risk. Specifically, we employ the following regression to test our primary hypothesis that climate risk weakens a fund's flow-performance sensitivity and estimate

$$FLOW_{i,t} = \gamma_1 PERF_{i,t-1} + \gamma_2 \log(CRI_{t-1}) + \gamma_3 PERF_{i,t-1} \text{x}\, CRI_t + \gamma_4 PERF - Squared_{i,t-1} + CONTROLS_{i,t} + U_i + \vartheta_t + \varepsilon_{i,t} \quad \textbf{(4)}$$

where $FLOW_{i,t}$ is the new money growth for fund *i* in month *t*, $PERF_{i,t-1}$ is the four-factor (CH-4) alpha for the fund and CRI_t is the climate risk index captured either by the Transition Risk Index (TRI) or Physical Risk Index (PRI) described earlier. In this formulation, a significant γ_2 captures the marginal effect of climate uncertainty on fund flows, while γ_3 is used to test whether higher climate uncertainty has any impact on the predictive power of past performance on subsequent flows. From an investor learning perspective, a negative and significant estimate for γ_3 would indicate that the funds' flow-performance sensitivities decrease with uncertainty, suggesting that higher climate uncertainty described in Section 2.2 hurts the informative role of past performance regarding managerial skills, thus weakening the signals for the predictability of future flows. However, considering that our measures of climate uncertainty capture climate risk from different aspects, one from a physical risk and the other from a transitional risk aspect, we estimated models separately for each type of risk to distinguish between the effect of each type of climate uncertainty on the sensitivity of fund flows to past performance. Finally, the model includes the fund and time fixed effects captured by u_i and v_t, respectively, to ensure the results are not driven by fund characteristics or time trends; the standard errors are also double clustered by fund and time.

In addition to controlling for the fund, country and time fixed effects in all our tests, we also include several non-performance-related control variables that have been shown to explain fund flows and their sensitivity to performance in the literature. Given the evidence that larger funds are expected to attract more flows (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Barber et al., 2005), we include log (Assets)$_{(t-1)}$ as a fund-level control variable. Likewise, following the argument in the literature that flow sensitivity to performance should be weaker for funds with longer track record i.e., older funds, we also control for fund age as a determinant of flows by including log (Fund Age)$_{(t-1)}$ in the model. As mentioned earlier, we also include the squared measure of performance ($PERF\_Squared_{i,t-1}$) in the model to account for the convex flow-performance relationship as it is found in the literature that flows respond asymmetrically to positive and negative performance. Following the evidence in the literature that return volatility weakens the flow performance sensitivity (Huang et al., 2022), another control variable included in the model is return volatility ($Volatility_{(t-1)}$) calculated as the time-series standard deviation of the fund's monthly returns over months t-*1* to t-*11*. Finally, following a number of papers including Renneboog, Horst and Zhang (2011), Ferreira, Keswani, Miguel and Ramos (2012), among others, to account for the mutual fund investment style in our tests, we include the Size, Market (MKT) and Momentum (WML) betas obtained by estimating 36- month rolling regressions of the Fama-French (2015) 5-factor model on raw fund returns. Note that all control variables are lagged by one-month.

3. Empirical Results

3.1. Fund flow-performance relationship

Table 3 presents the results for Equation 3 that the tests the effect of fund performance (in addition to several fund level controls) on monthly fund flows. Fund performance is measured by four-factor (CH-4) alphas and fund flows are based on Franzoni and Schmalz (2017). The explanatory variables with subscript (t-1) are lagged by one month. We report the findings for all funds in the sample and for funds in the Low, Medium and High ESG risk categories based on the sustainability ratings published by the Morningstar database. The results for all funds in the sample confirm the positive relationship between fund flows and past performance, indicating that fund flows respond positively to past performance, thus leading to money inflows to the funds. We find that every 1% increase in past performance of a fund predicts a 0.659% inflow. Interestingly, however, when we examine the results for funds across the ESG ratings, we find that the response of fund flows to past performance is stronger for low ESG risk, i.e., sustainable rated, funds, with every 1% increase in past performance predicting a 1.175% rise in money inflows into the funds. This is in contrast with the insignificant or weak flow-performance sensitivity observed for the high and average ESG risk funds, suggesting that investors learning regarding managerial ability to deliver in the future is relatively stronger for funds that have relatively stronger sustainability ratings. For these funds, consistent with the models of Berk and Green (2004) and Huang et al. (2022) where rational investors use past returns as a signal to form their posterior expectations about the ability of a fund manager, we find that this is more the case for funds that enjoy high ESG ratings.

While fund size is found to be negatively related to flows across all ESG categories, implying that larger funds tend to experience relatively lower money flows, we find that fund age is positively related to flows, suggesting that funds with longer histories tend to enjoy greater money flows as the older the fund, the more investors know about the manager's track record, thus providing valuable information for investors in their decision making to allocate their capital to these funds. Although return volatility seems to be insignificant for subsequent flow dynamics, we observe a negative and significant volatility effect on flows for high ESG risk funds, possibly as investors view higher ESG risk coupled with greater volatility in their past performance as a negative indicator of future performance, which in turn, negatively affects flows into these funds. Finally, further examining the coefficient of performance squared, we find a positive and statistically significant value for all funds (0.129), implying the presence of an asymmetric response of fund flows to past performance such that flows respond asymmetrically to good and poor past performance i.e., there is more inflow of money than outflow of money to the funds. This is consistent with the previous literature (see e.g., Chevalier and Ellison, 1997; Siri and Tufano, 1998, Busse, 2001; and Del Guercio and Tkac, 2002). Overall, while the benchmark model on the fund flow-performance relationship confirms the positive association between flows and performance, we observe some heterogeneity in the sensitivity of these funds when categorized based on their ESG ratings.

3.2. The effect of climate risk on the fund flow-performance sensitivity

As explained earlier, we test the effect of two types of climate risks (i.e., transitional risk, and physical risk) on the fund flow performance sensitivity via Equation 4. Panels A and B in Table 4 present the results for transition and physical climate risks, respectively. In each panel, we confirm the positive flow-performance relationship, suggesting that flows respond positively to past performance, indicated by the positive coefficient for *PERF*. Interestingly, however, when we examine the coefficients for *Climate Risk* (CRI), while transition climate risk is found to have a positive effect on flows in Panel A, we find that physical climate risk (Panel B) has the opposite effect on flows, with the strongest climate uncertainty effect on flows observed for low ESG risk funds. Considering that transition climate risk captures the uncertainty faced by certain institutions or sectors associated with the operational or regulatory changes driven by climate change (Cepni et al., 2023), the finding that flows respond positively to higher transition risk could be a manifestation of the preference by retail investors towards professional money management when it comes to managing their investment in the wake of regulatory or operational risks that affect firms. In contrast, physical climate risk materializes in a physical form wherein either extreme weather events or climate chronic hazards incur financial losses for the firm and the society (Bua et al. 2021, Cepni et al. 2022). Accordingly, the negative relationship between physical climate risk and flows could be due to the increased preference by investors towards safe haven assets like gold during periods of high physical climate uncertainties as investors move their investments out of risky equities during such periods of stress.

Further examining the interaction between the fund's past performance and climate uncertainty, $PERF_{(t-1)}$x CRI, we find that the interaction term is positive and significant for the entire sample of funds, consistently for both the transition and physical climate risk. This means that higher climate uncertainty, irrespective of its nature, makes fund flows more sensitive to past performance. When we split our sample based on the sustainability ratings, however, we see that the positive effect of the interaction between climate uncertainty and past performance on flows is primarily driven by funds that have low ESG risks. This finding suggests that high climate uncertainty drives greater allocation of capital to more sustainable funds as a result of favourable past performance, implying that investors attribute greater importance to past performance for ESG funds managers during periods of high climate uncertainty. Interestingly, however, we observe the opposite effect for high ESG risk funds and in the case of transition climate risk in Panel A. We find that the interaction between the fund's past performance and climate uncertainty has a negative effect on flows for high ESG risk funds, implying that when climate uncertainty is high, a one percentage point increase in fund return increases flows by significantly less than the case when climate uncertainty is low. This suggests that high transition climate risk dampens the flow-performance relationship, particularly in the case of low-quality sustainable funds, which means that investors' learning about the managerial skills of funds with high ESG risk is significantly affected by the climate uncertainty that is associated with the operational or regulatory changes faced by certain institutions or sectors of the economy. Overall, these results show that climate uncertainty indeed affects investor learning regarding managerial skills and this is particularly the case for funds that have greater ESG risks.

Tables 5a and 5b present the results for Equation 4 that tests the effect of climate risks and fund performance (in addition to several fund level controls) on monthly fund flows across the international and domestic funds. Panels A and B present the results domestic and international focused funds, respectively. As noted earlier, to classify the funds into international and domestic, we use the fund investment category from Morningstar. Tables 5a and 5b present the results based on transition and physical climate risk, respectively. Consistent with the findings reported in Table 4, we find that flows respond positively (negatively) to higher transition (physical) climate uncertainty, consistently across both the international and domestic focused funds. This finding further supports our earlier inferences that the effect of climate uncertainty on money flows in and out of professionally managed funds is indeed dependent on the nature of the climate risk in the form of its physical or transitional nature. Interestingly, we observe that past performance is less of a concern for international focused funds implied by the insignificant coefficients for *PERF* in Panel B in both tables. In the case of domestic funds, however, we find that past performance is a strong predictor of flows only for funds with high ESG risk. This means that when investors evaluate funds with poor ESG performance, they place more emphasis on the past performance of these funds as an indicator of managerial skills whereas past performance becomes less of a concern regarding managerial skills when it comes to funds with superior ESG performance. This is indeed consistent with the evidence that environmental and social investments have been quite resilient during the COVID-19 crisis (Albuquerque et al., 2020) and investors remained focused on sustainability even during periods of high uncertainty (Pastor and Vorsatz, 2020; Yousaf et al., 2022).

Examining the interaction between the fund's past performance and climate uncertainty, however, we find that the effect of climate uncertainty on the flow-performance relationship is largely restricted to domestic funds rather than their international focused counterparts. It could be argued that the enhanced diversification offered by international focused funds alleviates the climate related concerns of investors and climate uncertainty becomes less of a factor when it comes to assessing managerial skills in the context of past performance for these funds. For domestic funds, however, we find in Panel A of Table 5a that the interaction term is positive and significant for low ESG risk funds whereas the opposite holds for high ESG risk funds. This means that high climate uncertainty hinders investor learning, particularly when it comes to funds with poor ESG performances, dampening the flow-performance relationship for those funds. In contrast, we observe the opposite pattern for low ESG risk funds with a positive interaction term, suggesting that past performance becomes more of an indicator of managerial skills for these funds under high climate uncertainty. Considering that high ESG ratings for a fund indicates greater transparency and information available for investors regarding fund holdings and characteristics, thus alleviating information asymmetries between the investors and fund managers, one can argue that investors feel more confident to use past performance as an indicator of managerial skills for these highly rated funds during periods of high climate uncertainty. In contrast, for funds with poor ESG ratings, high climate uncertainty hinders investors' learning regarding the investment skills of fund managers, thus making past performance less of an indicator for future performance. Overall, our findings show that climate uncertainty indeed plays a significant role over investor learning regarding managerial skills. However, the role played by climate uncertainty depends on the ESG performance of these funds and the nature of climate risk. Furthermore, transition climate risk that captures the uncertainty faced by investors regarding the operational and/or regulatory implications of climate change on firms and sectors of the economy, is found to be a more dominant determinant of the fund flow-performance sensitivity of managed funds, consistent with the evidence in Faccini et al. (2021) that transition climate risk is a dominant driver of stock returns compared to physical climate risk.

4. Robustness checks and supplementary analyses

4.1. Climate risk and asymmetries in fund flow-performance sensitivity

To ensure that our results and inferences regarding the effect of climate uncertainty on the fund flow-performance relationship are robust, we perform several additional tests. First, we re-examine our main hypothesis (i.e., uncertainty effect on the flow-performance sensitivity of a fund) by employing an alternative specification along the lines of Bollen (2007) and Renneboog, Horst and Zhang (2011). This supplementary analysis not only allows us to check the robustness of our findings obtained from the models described in Equations 3 and 4, but also broadens our understanding of the nexus between climate uncertainty and fund flow performance sensitivity by accounting for possible asymmetries in the flow-performance relationship with respect to the sign of the past returns. The benchmark specification in this alternative approach is formulated as

$$FLOW_{i,t} = (\varphi_1 R^{+} + \varphi_2 R^{-})Return_{i,[t-1,t-12]} + CONTROLS_{i,t} + \theta_i + \tau_t + e_{i,t} \qquad \textbf{(5)}$$

where $FLOW_{i,t}$ is the new money growth for fund i in month t, $Return_{i,[t-1,t-12]}$ is the average CH-4 alpha of fund i over months [t-1, t-12] and R^+ and R^- are indicator variables that equal one if the CH-4 alpha is non-negative or negative, respectively. In this formulation, positive and significant values for φ_1 and φ_2 would indicate that fund flows follow the direction of past performance in a symmetric fashion such that positive (negative) past performance predicts fund inflows (outflows) in the following month. Note that we account for the fund and time fixed effects by including θ_i and τ_t in the model, respectively and estimated the standard errors as double clustered by fund and time.

Next, to examine the effect of climate uncertainty on the sensitivity of fund flows to past performance, we augment the benchmark model in Equation 5 by incorporating climate risk in the model as

$$FLOW_{i,t} = (\varphi_1 R^+ + \varphi_2 R^-)Return_{i,[t-1,t-12]} + (\varphi_3 R^+ + \varphi_4 R^-)Return_{i,[t-1,t-12]} * CRI_t + CONTROLS_{i,t} + \theta_i + \tau_t + e_{i,t} \quad \textbf{(6)}$$

where CRI_t is the climate risk index captured either by the Transition Risk Index (TRI) or Physical Risk Index (PRI) described in Section 2.2. In this augmented formulation, negative and significant estimates for φ_3 and φ_4 indicate that the funds' flow-performance sensitivities decrease with uncertainty, suggesting that higher climate uncertainty hurts the informative role of past performance regarding managerial skills, thus weakening the signals for the predictability of future flows. As mentioned earlier, one advantage of this alternative approach is that it allows us to separate the effect of good past performance (positive return) from the effect of bad past performance (negative return) on subsequent fund flows and investigate possible asymmetries in investor learning with respect to the sign of past fund performance.

Table 6 presents the results for Equation 5 based on the specification by Bollen (2007) and Renneboog, Horst and Zhang (2011). We observe that fund flows respond strongly to positive past returns, implied by the positive and significant φ_1 estimates. We find for the overall sample of funds that every 1% percent increase in past returns (in the positive direction) leads to a 1.559% increase in the inflow of funds subsequently. However, this pattern applies primarily to funds with low ESG risk, supporting our previous inference that ESG performance of a fund tends to enhance investor learning regarding managerial skills, making their flows more sensitive to past performance. For funds with average and high ESG risk, however, we find that the estimated φ_1

values become smaller, eventually turning insignificant for high ESG risk funds. The difference in response between low and high ESG risk categories is consistent with the evidence by Bollen (2007) and Renneboog et al. (2011) who argue that investors in low ESG risk funds (sustainable funds) consider non-financial attributes (ESG attributes) while making investment allocations decisions, however, their capital allocation decision is conditional on the past performance so that when a fund's past performance is favourable, investors use this as a signal to confirm the ability of the fund manager. This argument is further supported by the finding that the fund flow response to negative returns is insignificant for all fund categories with the exception of low ESG risk funds for which we find that past performance serves as a predictor of subsequent fund flows in both cases. The additional results, thus, provide further insight to our previous findings, highlighting the ESG classification of a fund as a driver of investor learning regarding managerial skills.

Further extending our analysis to the role of climate risk, we present the results for Equation 6 in Table 7, which tests the effect of transition (physical) climate risks and fund performance (in addition to several fund level controls) on monthly fund flows based on the alternative specification by Bollen (2007) and Renneboog. Panels A and B report the findings for the transition (TRI) and physical (PRI) climate risks, respectively. While the findings confirm the informative role of past performance on subsequent flows, particularly for low ESG risk funds, we find that the interaction term for positive past returns (φ_3) is positive and significant for low ESG risk funds and only in the case of transition climate risk in Panel A. This means that higher uncertainty regarding the transitional implications of climate change in the economy, makes flows to low ESG risk funds more sensitive to past performance. In other words, high transition risk contributes to investor learning for more sustainable funds, particularly when past performance is favourable. In contrast, we find that poor past performance plays a more informative role primarily for high ESG risk funds, providing signals regarding managerial skills, thus capturing predictive information regarding future flows. Overall, the additional tests provide further insight to our analysis in that investor learning is affected by not only the nature of climate uncertainty faced by the economy, but also the sustainability of the fund under consideration.

In Tables 8a and 8b, we further explore the role of climate uncertainty in international and domestic funds by re-estimating Equation 6 for domestic (Panel A) and international (Panel B) focused funds, using transitional and physical climate risk as sources of climate uncertainty, respectively. In Panel A, we observe that climate risk, irrespective of its nature as transition or physical risks, plays a significant role on investor learning, particularly for domestic funds with low ESG ratings (high ESG risk). High climate risk dampens the sensitivity of domestic fund flows to past performance when past performance is good, implied by a negative and significant φ_3 estimate for domestic funds in both tables. This suggests that when evaluating high ESG risk funds with a domestic focus, investors see lesser value in favourable past performance when challenged with greater climate uncertainty, which in turn makes these funds' flows less sensitive to past performance. This implies that high climate uncertainty in fact hinders investor learning in domestic funds that have low ESG ratings. In contrast, significant and positive φ_4 estimates for high ESG risk funds in Panel A of both tables imply that high climate uncertainty enhances fund flow-performance sensitivity when past performance is poor, suggesting that investors attribute greater importance to poor past performance regarding managerial skills in high ESG risk funds when faced with climate uncertainty. This inference also applies to international focused funds in Panel B, suggesting that past poor performance plays an even more important predictive role for managerial skills when investors evaluate high ESG risk funds under high climate uncertainty.

Finally, as supplementary checks, we conduct two additional tests. First, we re-estimate our models by using an alternative approach to estimate fund alphas based on the country level risk factors rather than regional risk factors that we used in our main analysis. To that end, we first obtained the country specific risk factors for Australia and New Zealand from the data library of Jensen, Kelly, and Pedersen (2022).[9] Next, we re-estimated the four-factor fund alphas via $R_{i,c,t} - \beta_i^{mkt} MKT_m + \beta_i^{smb} SMB_m + \beta_i^{hml} HML_m + \beta_i^{mom} MOM_m$ where the risk factors are the country-specific factors. As a second robustness check, we re-estimated our models by replacing the climate risk index used in our tests with an alternative climate risk index (CRI_NW) that is constructed similarly to the original indexes via textual analysis but excludes the news articles published on the weekends. The rationale behind this alternative measure is that excluding the news articles published over the weekend allows us to mitigate possible stale information effects on market prices since timelier public information results in a closer alignment of information sets

[9] The data for country specific risk factors can be found at https://jkpfactors.com/.

of traders (Gropp and Kadareja, 2012). Although we do not report these additional tests to save space, we find that our results continue to hold and yield similar inferences.[10]

4.2. Sensitivity to climate risk and fund characteristics

To provide further insight to the interaction between climate risk and the flow-performance sensitivity of funds, in the final step of our analysis, we explore whether funds whose flows are more sensitive to climate uncertainty display markedly different features compared to funds whose flows are less sensitive. Given the evidence presented so far that climate uncertainty plays a significant role in investor learning, it is possible that certain fund features that are associated with the climate betas of these funds drive the observed interaction between climate uncertainty and investor learning. To that end, we first sort the entire sample of funds into quintiles based on the sensitivity of their net flows to climate uncertainty by employing a 36-month rolling window regression as

$$NF_{i,t} = \alpha_{i,t} + \beta_{i,t}^{c} CRI_t + \varepsilon_{i,t} \qquad \textbf{(7)}$$

where $NF_{i,t}$ is the net flow for fund *i* in month *t*, CRI_t is the climate risk (transition – TRI or physical – PRI) in month *t*, and $\beta_{i,t}^{c}$ is the climate beta for fund *i* in month *t*. Using the estimated climate betas, we then sort the funds in the sample into value-weighted quintile portfolios where Quintile 5 (1) contains funds whose flows are the most (least) sensitive to climate uncertainty.

Table 9 reports the univariate distribution of fund returns along with other fund characteristics of the quintile portfolios based on their climate betas reported in the second column in each panel. Panels A and B report the results for funds sorted on their sensitivity to transition (TRI) and physical (TRI) climate uncertainty, respectively. We observe in both panels that funds whose flows are more sensitive to climate uncertainty yield significantly higher raw and risk-adjusted returns. The return spread between high and low climate beta funds is 0.272% and 0.153% per month, in Panels A and B, respectively. These numbers are highly significant both statistically and economically and remain significant even after adjustment for risk based on the Carhart four factor model. The positive risk premium associated with climate sensitivity of fund flows is in fact in line with the recent evidence that climate risk exposure serves as a systematic driver of equity

[10] The results for these supplementary tests are available upon request from the authors.

returns (Faccini et al., 2021; Bolton and Kacperczyk, 2021; Bua et al., 2021; Hsu et al., 2023). While funds that are more sensitive to climate uncertainty experience greater flows than funds that are less sensitive to climate uncertainty, interestingly, we find that higher climate sensitivity is generally associated with lower idiosyncratic volatility, downside risk and fund return volatility. Accordingly, one can argue that the climate uncertainty effect on the flow-performance relationship of funds could be driven by the sensitivity of the fund flows to climate shocks, which in turn, drives the risk and return profiles of these funds.

5. Conclusion

This paper presents a novel take on how uncertainty affects investor learning regarding managerial skills by examining the role of climate uncertainty on the fund flow-performance relationship in ESG rated funds. Specifically, building on the argument that investors use past fund performance as a signal to infer fund managers' ability to generate returns in the future and utilizing a bias-free mutual fund dataset that includes all available open-end funds from Morningstar Direct for the universe of funds domiciled in Australia and New Zealand, we test whether climate uncertainty dampens the sensitivity of a fund's flows to past performance across the funds with high and low ESG ratings. To that end, we first develop two novel indexes of climate risk for the Australia-Oceania region via textual analysis of an extensive list of news articles from *The Australian* and *The New Zealand Herald* associated with the region over the period 2018-2022. Using the physical and transition climate risk weighted vocabularies of Bua et al. (2021) and the cosine-similarity approach of Engle et al. (2020), we then generate novel physical and transition climate risk indexes for Australia-Oceania. Our procedure is able to capture the distinction between physical and transition risks associated with climate change as the former captures various acute physical risks such as extreme weather events associated with the region, while the latter captures the developments that are more related to the operational, regulatory or policy implications of climate change.

While our findings confirm the established evidence that fund flows respond positively to past performance, we find that the nature of climate uncertainty, in terms of transition or physical risk, and the ESG rating of the fund play a significant role on the sensitivity of fund flows to past performance. Specifically, we find that the response of fund flows to past performance is particularly stronger for low ESG risk funds, i.e., funds with higher sustainability scores, suggesting that rational investors use past returns as a signal to form their posterior expectations about the ability of a fund manager, more so when a fund enjoys high ESG ratings. In contrast, we find that high transition climate risk dampens the flow-performance relationship, particularly in the case of funds with poor sustainability ratings, implying that investor learning about managerial skills in funds with high ESG risk is significantly hindered by the type of climate uncertainty that is associated with the operational or regulatory changes faced by certain institutions or sectors of the economy. We argue that favourable ESG performance for a fund helps to mitigate information asymmetries between the investors and fund managers, which in turn makes investors more confident to use past performance as an indicator of managerial skills for highly rated funds during periods of high climate uncertainty. Further classifying funds based on their domestic or international focus, we find that the effect of climate uncertainty on the flow-performance relationship is largely restricted to domestic funds rather than their international focused counterparts. We argue that the enhanced diversification offered by international focused funds alleviates the regional climate concerns of investors which makes climate uncertainty less of a factor when it comes to assessing managerial skills in the context of past performance for these funds.

Further analysis shows that investors reward funds in an asymmetric fashion based on their past performance when faced with uncertainty. We find that high transition risk contributes to investor learning for funds with higher sustainability scores, particularly when past performance is favourable. This means that investors attribute greater weight to favourable past performance when they make capital allocation decisions to low ESG risk funds under high transition climate uncertainty, highlighting the role of favourable past performance for these funds regarding managerial skills. In contrast, we find that poor past performance plays a more informative role under high climate uncertainty, primarily for high ESG risk funds, providing signals regarding managerial skills, thus capturing predictive information regarding future flows. Overall, our analysis shows that investor learning is affected by not only the nature of climate uncertainty faced by decision makers, but also the sustainability ratings of the funds under consideration.

Our findings provide novel insight to the emerging literature on the effect of climate risk in financial markets by establishing evidence that climate uncertainty plays a significant role on investor learning regarding fund manager ability based on signals from past performance. In particular, the findings highlight the informational value captured by ESG ratings on investor learning, particularly when faced with higher climate risks that affect the economy both from a physical and regulatory perspective. Although the evidence in the literature generally suggests that high uncertainty dampens investors' ability to process information regarding managerial skills, our findings show that this learning process in fact could be enhanced by the ESG performance of funds, even under high uncertainty. While climate uncertainty serves as a significant determinant of fund flows as a standalone factor, particularly for funds that enjoy favourable sustainability ratings, our findings show that high climate risk dampens investors' ability to process information when it comes to funds with poor ESG performance, thus hindering their ability to differentiate fund manager ability from luck. These findings have significant implications for the managed fund industry and the information asymmetries that may arise between fund managers and investors. Future research could benefit from further exploring the fund characteristics that make fund flows more sensitive to uncertainty in the hope that we can broaden our understanding of the effect of climate uncertainty on investor learning and capital allocation decisions.

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Figure 1. The distribution of mutual funds across the sustainability (ESG) ratings.

The figure presents the distribution of mutual funds in the sample across the five ESG ratings over the period 2018-2022. The sustainability globe ratings represent funds with high ESG risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). As shown in Figure A1 in the Appendix, a fund with high (low) ESG risk relative to its Morningstar Global Category receives 1 (5) globe.

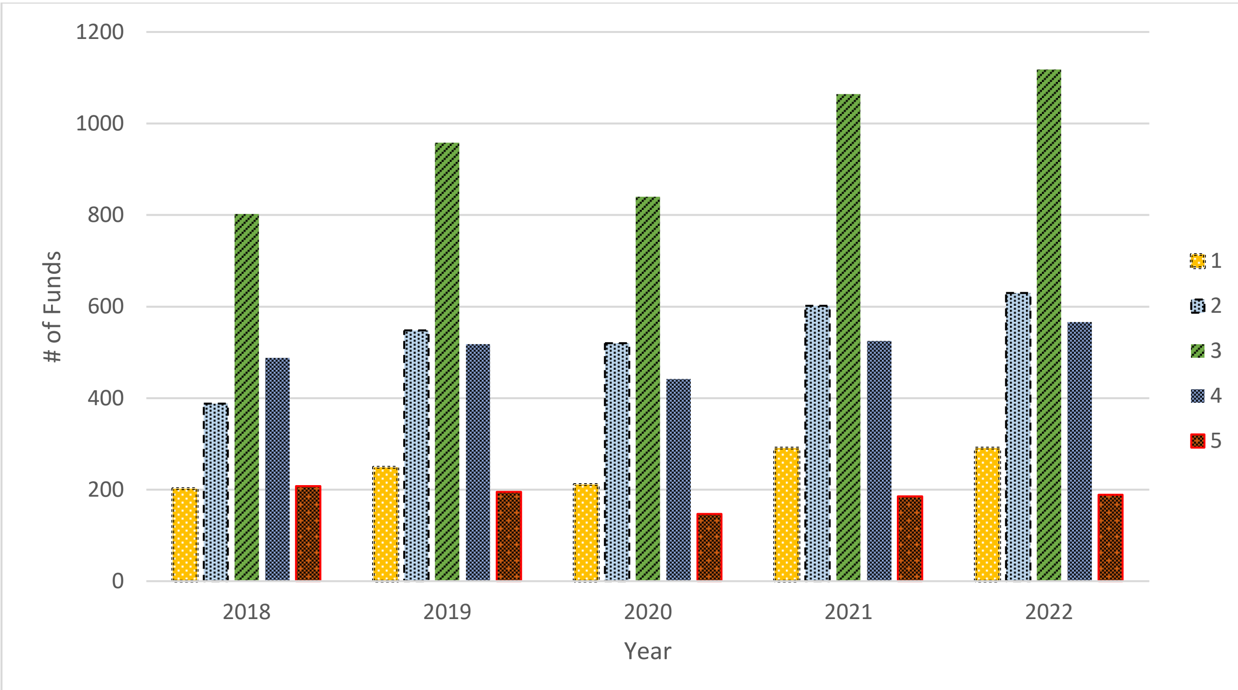
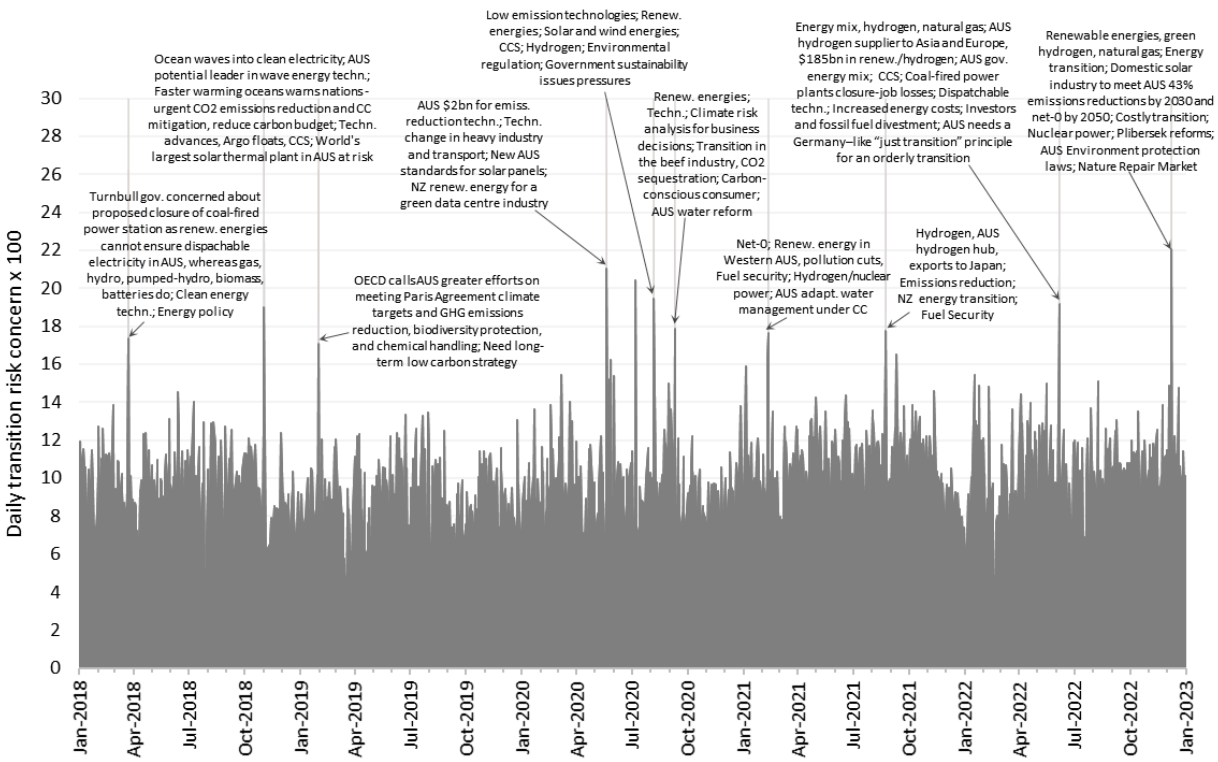


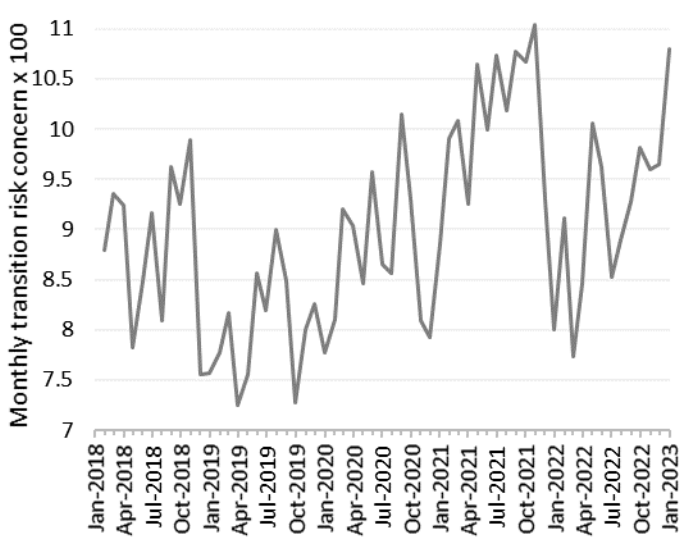
Figure 2. Transition climate risk 2018-2022.

This figure presents daily transition risk concern (Panel A) and major risk shock topics (vertical bars), monthly transition concern (Panel B), and TRI (Panel C) time series from Jan 2018 to Dec 2022. *The Australian* and *The New Zealand Herald* news with an Australia-Oceania regional focus. "CC" acronym for "climate change".

Panel A: Daily transition climate risk



Panel B: Monthly transition risk concern



Panel C: Monthly transition risk index (TRI)

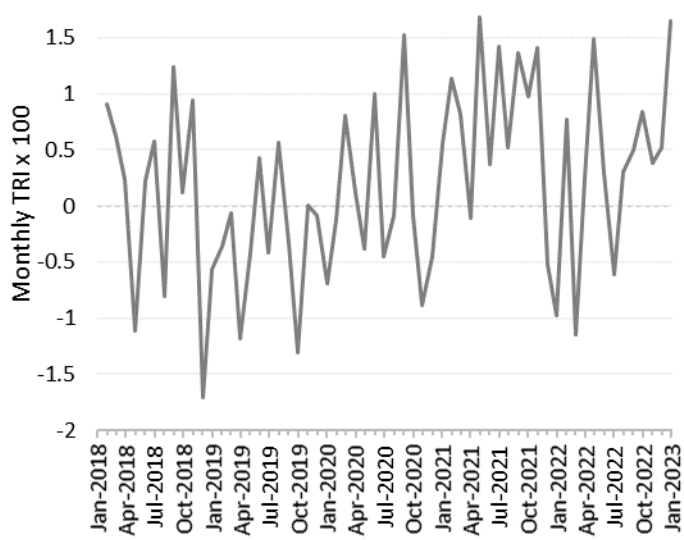
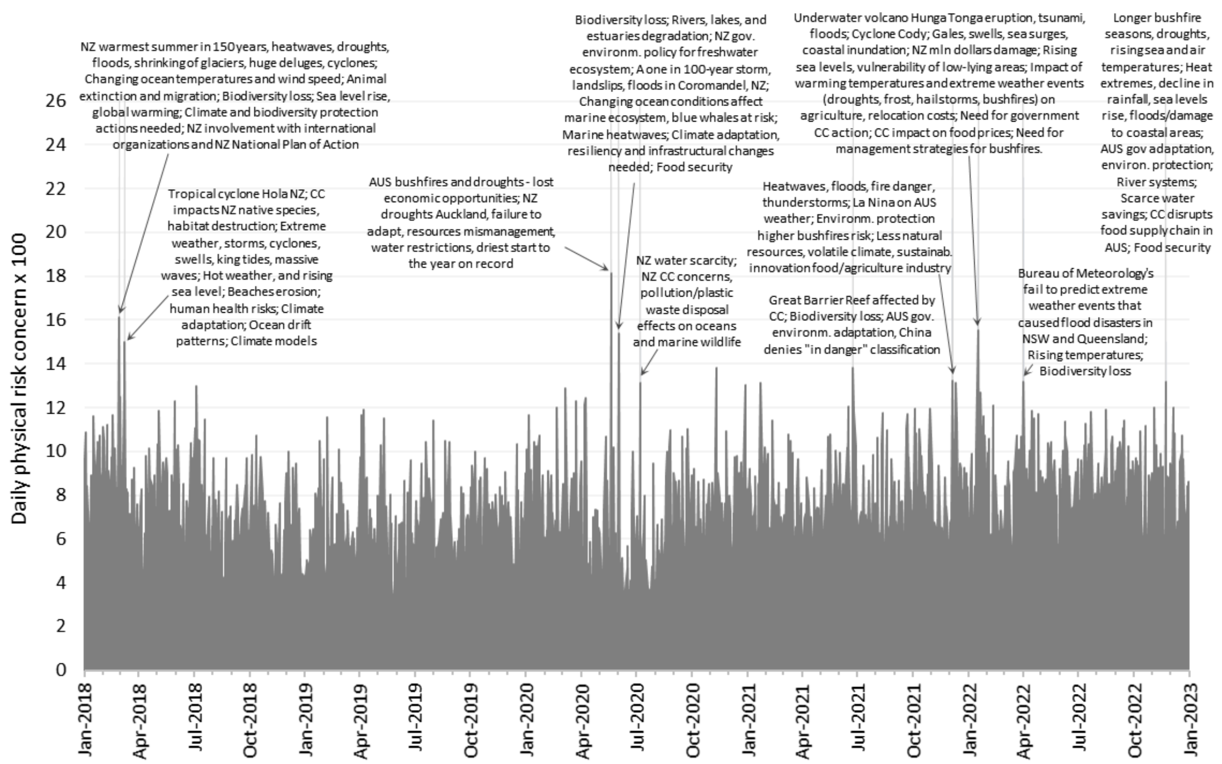


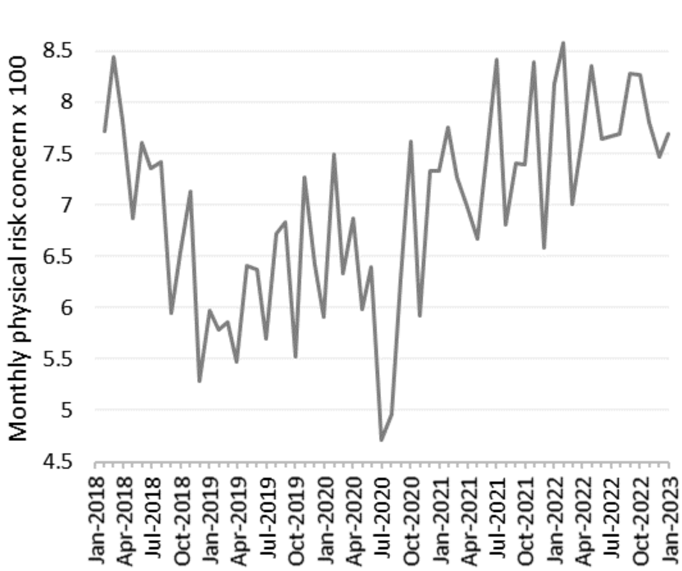
Figure 3. Physical climate risk 2018-2022.

This figure presents daily physical risk concern (Panel A) and major risk shock topics (vertical bars), monthly physical concern (Panel B), and PRI (Panel C) time series from Jan 2018 to Dec 2022. *The Australian* and *The New Zealand Herald* news with an Australia-Oceania regional focus. "CC" acronym for "climate change".

Panel A: Daily physical climate risk



Panel B: Monthly physical risk concern



Panel C: Monthly physical risk index (PRI)

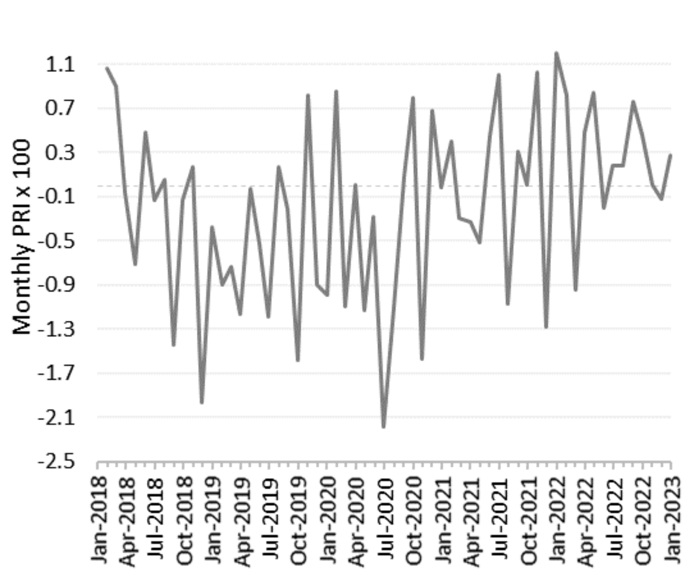


Table 1. Descriptive statistics for fund performance, fund size and flows

This table presents the monthly averages of fund performance (raw returns), fund size and fund flows each year for the full sample (Panel A) and the monthly fund statistics across the five Morningstar sustainability ratings (Panel B). Monthly fund flows (%) are computed based on Franzoni and Schmalz (2017) as $FLOW_{i,c,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+R_{i,t})}{TNA_{i,t-1}}\ x\ 100$ where $TNA_{i,t}$ is the total net assets (Size) in USD of fund i at the end of month t, and $R_{i,t}$ is the return of fund i in month t. Panel B presents the average fund performance (monthly raw returns (%) $_{(t)}$), monthly fund flows and fund size for funds across the five sustainability ratings. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). A fund with high (low) ESG risk relative to its Morningstar Global Category receives 1 (5) globe. The last column in the panel shows the difference between high and low ESG risk rated funds along with the corresponding t-statistics in parenthesis. Values for raw returns, size and fund flow are winsorized at 1% and 99%. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fund performance and flows over time			
Year	Monthly Raw returns (%) $_{(t)}$	Fund Flow (%) $_{(t)}$	Size (Mn) $_{(t)}$
2018	-2.72	-0.17	168.14
2019	1.73	-0.65	170.21
2020	1.94	-0.52	156.10
2021	0.52	-1.31	212.44
2022	-1.15	-0.93	192.91
All years	0.06	-0.72	179.96
Panel B: Fund performance and flows across the five sustainability ratings			
Ratings	Monthly Raw returns (%) $_{(t)}$	Fund Flow (%) $_{(t)}$	Size Mn $_{(t)}$
High risk	0.68	-0.63	148.87
2	0.40	-0.81	179.35
3	0.50	-0.93	204.93
4	0.45	-0.66	160.43
Low risk	0.34	-0.70	172.53
High – Low	0.34***	0.08	-23.67**
t-stat	(2.90)	(0.72)	(-2.47)

Table 2. Descriptive statistics of mutual funds in the sample

Panels A, B and C present the summary statistics of the mutual fund characteristics for the whole sample, low-risk and high-risk funds, respectively. Fund performance is measured by four-factor (CH-4) alphas. Fund flows are based on Franzoni and Schmalz (2017). Fund Size is log(assets). Fund Age is the total number of months in fund's existence. Idiosyncratic volatility is computed relative to the benchmark Fama-French (2015) 5-factor model via rolling regressions as per Ang et al. (2016). Size, MKT and WML betas are coefficients obtained through 36- month rolling regressions of the Fama-French (2015) 5-factor model on raw fund returns that capture the fund investment styles tilted towards size, market and momentum portfolios respectively. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

Panel A: Full sample							
	Mean	Std. Dev.	Min.	p25	Median	p75	Max.
$FLOW$	-0.797***	5.874	-20.986	-1.687	-0.374	0.499	17.51
CH-4 Alpha	0.339***	0.446	-0.639	0.08	0.352	0.615	1.255
Raw returns	0.537***	7.042	-22.38	-2.95	1.11	4.74	17.58
Volatility	5.935***	2.738	2.383	4.014	5.181	7.007	14.449
Fund Size	3.033***	2.415	-2.761	1.327	3.183	4.854	7.786
Fund Age (Months)	5.014***	0.602	3.466	4.691	5.124	5.434	6.035
Idiosyncratic Volatility	2.689***	1.079	1.167	1.911	2.416	3.162	5.548
Size Beta	-0.018***	0.251	-0.663	-0.162	-0.021	0.131	0.594
MKT Beta	0.884***	0.146	0.51	0.807	0.892	0.968	1.259
WML Beta	-0.105***	0.21	-0.555	-0.247	-0.11	0.022	0.442
Panel B: Low risk funds							
	Mean	Std. Dev.	Min.	p25	Median	p75	Max.
$FLOW$	-0.704***	5.992	-20.986	-1.669	-0.402	0.498	19.014
CH-4 Alpha	0.412***	0.448	-0.941	0.175	0.43	0.689	1.407
Raw returns	0.435***	6.962	-20.25	-3.01	0.68	4.45	17.48
Volatility	5.927***	2.584	2.457	4.14	5.264	6.975	13.722
Fund Size	3.098***	2.194	-1.433	1.411	3.263	4.886	8.398
Fund Age (Months)	4.952***	0.642	3.434	4.543	5.112	5.425	6.061
Idiosyncratic Volatility	2.881***	1.135	1.179	2.117	2.597	3.289	6.137
Size Beta	0.158***	0.263	-0.638	0.014	0.19	0.32	0.718
MKT Beta	0.911***	0.15	0.561	0.827	0.91	1.006	1.206
WML Beta	-0.104***	0.241	-0.59	-0.267	-0.129	0.044	0.498
Panel C: High risk funds							
	Mean	Std. Dev.	Min.	p25	Median	p75	Max.
$FLOW$	-0.626***	5.656	-20.986	-1.595	-0.31	0.621	17.422
CH-4 Alpha	0.32***	0.454	-0.599	-0.024	0.298	0.671	1.298
Raw returns	0.619***	7.845	-34.53	-2.95	1.04	4.87	19.78
Volatility	6.391***	3.608	2.219	3.86	5.112	7.597	16.15
Fund Size	3.016***	2.535	-4.491	1.718	3.397	4.738	7.737
Fund Age (Months)	5.069***	0.597	3.497	4.762	5.176	5.533	5.976
Idiosyncratic Volatility	2.898***	1.07	1.262	2.086	2.633	3.451	5.402
Size Beta	-0.152***	0.268	-0.657	-0.351	-0.157	0.019	0.521
MKT Beta	0.799***	0.127	0.522	0.717	0.807	0.877	1.074
WML Beta	-0.064***	0.261	-0.598	-0.257	-0.09	0.101	0.536

Table 3. Mutual fund flows and performance

The table presents the results for Equation 3 that the tests the effect of fund performance (in addition to several fund level controls) on monthly fund flows. Fund performance is measured by four-factor (CH-4) alphas. Fund flows are based on Franzoni and Schmalz (2017). The explanatory variables with subscript (t-1) are lagged by one month. Low, Medium and High-risk funds are based on the sustainability ratings published by the Morningstar database. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). All models include country, fund and time fixed effects. The robust p-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

Dependent variable	Fund Flow$_{(t)}$			
Perf:	CH4- Alpha			
	All Funds	Low Risk	Average Risk	High Risk
PERF $_{(t-1)}$	0.659***	1.175***	0.332	0.750*
	(0.000)	(0.005)	(0.158)	(0.094)
PERF-Squared $_{(t-1)}$	0.129***	0.052	0.406**	-0.095
	(0.000)	(0.872)	(0.033)	(0.808)
Volatility	-0.007	-0.015	0.104***	-0.174***
	(0.714)	(0.851)	(0.007)	(0.001)
log (Assets) $_{(t-1)}$	-0.759***	-1.052***	-0.859***	-1.477***
	(0.000)	(0.000)	(0.000)	(0.000)
log (Fund Age) $_{(t-1)}$	0.547*	8.660***	1.487**	2.951**
	(0.094)	(0.000)	(0.016)	(0.015)
Size Beta	2.084***	3.431***	2.248***	3.752***
	(0.000)	(0.000)	(0.000)	(0.000)
MKT Beta	-1.506***	-4.183***	-0.592	0.315
	(0.000)	(0.002)	(0.345)	(0.820)
WML Beta	1.767***	2.292***	2.296***	2.956***
	(0.000)	(0.002)	(0.000)	(0.000)
Intercept	1.683	-33.669***	-3.979	-8.022
	(0.292)	(0.000)	(0.197)	(0.182)
N	59,770	4,921	24,003	7,071
R-Squared	0.183	0.214	0.190	0.208
Country Fund and Time FE	Yes			

Table 4. Climate risks and fund-flow-performance relationship

Panels A (B) present the results for Equation 4, that the tests the effect of transition (physical) climate risks and fund performance (in addition to several fund level controls) on monthly fund flows. Climate risks (CRI) are captured by the transitional risk index (TRI) and physical risk index (PRI) described in Section 2.2 and reported in Panels A and B, respectively. Fund performance is measured by four-factor (CH-4) alphas. Fund flows are based on Franzoni and Schmalz (2017). The explanatory variables with subscript (t-1) are lagged by one month. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). All models include country and time fixed effects. The robust p-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

	Panel A: Transitional climate risk index (**TRI**)				**Panel B:** Physical climate risk index (**PRI**)			
	All Funds	Low Risk	Average Risk	High Risk	All Funds	Low Risk	Average Risk	High Risk
PERF *(t-1)*	0.628***	0.937**	0.349	0.802*	0.706***	1.277***	0.325	0.815*
	(0.000)	(0.027)	(0.140)	(0.074)	(0.000)	(0.002)	(0.171)	(0.070)
Climate Risk (CRI)	2.116***	4.152***	2.361***	2.278***	-3.185***	-6.514***	-3.457***	-3.640***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PERF *(t-1)* x Climate Risk	0.19**	0.74***	-0.11	-0.47*	0.257***	0.674***	-0.031	0.382
	(0.013)	(0.004)	(0.471)	(0.096)	(0.000)	(0.007)	(0.829)	(0.118)
PERF-Squared *(t-1)*	0.117***	0.111	0.409**	-0.057	0.122***	0.040	0.408**	-0.134
	(0.000)	(0.733)	(0.032)	(0.885)	(0.000)	(0.903)	(0.033)	(0.732)
Volatility *(t-1)*	-0.007	-0.015	0.104***	-0.177***	-0.008	-0.010	0.104***	-0.176***
	(0.734)	(0.848)	(0.007)	(0.001)	(0.694)	(0.899)	(0.007)	(0.001)
log (Assets) *(t-1)*	-0.761***	-1.103***	-0.858***	-1.469***	-0.766***	-1.113***	-0.859***	-1.488***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
log (Fund Age) *(t-1)*	0.544*	8.883***	1.481**	2.975**	0.551*	8.836***	1.485**	2.982**
	(0.096)	(0.000)	(0.017)	(0.015)	(0.092)	(0.000)	(0.017)	(0.014)
Size Beta *(t-1)*	2.085***	3.402***	2.254***	3.751***	2.093***	3.508***	2.248***	3.800***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT Beta *(t-1)*	-1.505***	-4.114***	-0.580	0.356	-1.536***	-4.409***	-0.586	0.217
	(0.000)	(0.003)	(0.355)	(0.797)	(0.000)	(0.001)	(0.350)	(0.876)
WML Beta *(t-1)*	1.741***	2.247***	2.309***	3.037***	1.709***	2.278***	2.304***	2.800***
	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)
Intercept	-17.98***	-73.43***	-25.84***	-29.21***	-2.159	-41.854***	-8.298**	-12.475*
	(0.000)	(0.000)	(0.000)	(0.002)	(0.208)	(0.000)	(0.012)	(0.055)
N	59,770	4,921	24,003	7,071	59,770	4,921	24,003	7,071
R-Squared	0.183	0.215	0.190	0.209	0.183	0.215	0.190	0.209
Country, Fund and Time FE				Yes				

Table 5a. Investment focus, climate risks and fund-flow-performance relationship

This table presents the results for Equation 4 that tests the effect of climate risks and fund performance (in addition to several fund level controls) on monthly fund flows across the international and domestic funds. Panels A and B present the results domestic and international focused funds, respectively. To classify the funds into international and domestic, we use the fund investment category from Morningstar. Climate risks are by the transition (TRI) and physical (PRI) risk indexes described in Section 2.2. Tables 5a and 5b present the results based on transition and physical climate risk, respectively. Fund performance is measured by four-factor (CH-4) alphas. Fund flows are based on Franzoni and Schmalz (2017). The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). The explanatory variables with subscript (t-1) are lagged by one month. All models include country, fund and time fixed effects. The robust p-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

	Panel A: Domestic funds				**Panel B:** International funds			
	All Funds	Low Risk	Average Risk	High Risk	All Funds	Low Risk	Average Risk	High Risk
PERF $_{(t-1)}$	0.529***	0.715	0.298	1.296**	0.010	0.184	-0.589	1.512
	(0.000)	(0.305)	(0.323)	(0.013)	(0.967)	(0.765)	(0.203)	(0.387)
Transition Risk (TRI)	2.046***	4.018***	2.624***	1.402*	2.353***	5.155***	2.432***	2.327*
	(0.000)	(0.000)	(0.000)	(0.054)	(0.000)	(0.000)	(0.000)	(0.065)
PERF $_{(t-1)}$ x TRI	0.026***	0.082**	0.003	-0.116***	0.035**	0.069	0.024	0.071
	(0.005)	(0.012)	(0.904)	(0.002)	(0.038)	(0.114)	(0.432)	(0.337)
PERF-Squared $_{(t-1)}$	0.092***	0.720	0.259	0.016	0.690***	-0.437	0.944***	-0.227
	(0.001)	(0.142)	(0.268)	(0.971)	(0.000)	(0.377)	(0.007)	(0.873)
Volatility $_{(t-1)}$	-0.054*	-0.222*	0.152***	-0.168**	-0.019	0.343*	0.050	-1.214***
	(0.052)	(0.067)	(0.008)	(0.017)	(0.750)	(0.055)	(0.634)	(0.000)
log (Assets) $_{(t-1)}$	-1.047***	-0.831**	-1.181***	-1.118***	-0.479***	-1.297***	-0.529***	-2.128***
	(0.000)	(0.040)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)
log (Fund Age) $_{(t-1)}$	1.782***	7.907***	3.637***	0.866	-1.116**	9.904***	-0.969	6.544**
	(0.000)	(0.000)	(0.000)	(0.554)	(0.043)	(0.000)	(0.298)	(0.025)
Size Beta $_{(t-1)}$	1.904***	2.229**	2.513***	2.658***	3.747***	7.229***	4.080***	6.705***
	(0.000)	(0.012)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
MKT Beta $_{(t-1)}$	-1.004**	-3.164	-1.641*	-1.409	-4.722***	-9.970***	-5.323***	7.496*
	(0.034)	(0.130)	(0.077)	(0.449)	(0.000)	(0.000)	(0.000)	(0.067)
WML Beta $_{(t-1)}$	1.858***	1.863*	2.418***	2.878***	1.123***	0.945	1.663***	-0.149
	(0.000)	(0.062)	(0.000)	(0.000)	(0.004)	(0.486)	(0.009)	(0.949)
Intercept	-23.11***	-69.72***	-37.32***	-11.61	-10.28**	-81.77***	-11.37	-42.80**
	(0.000)	(0.000)	(0.000)	(0.327)	(0.017)	(0.000)	(0.122)	(0.037)
N	38,693	2,401	15,162	5,630	21,077	2,520	8,841	1,441
R-Squared	0.181	0.231	0.189	0.172	0.189	0.210	0.199	0.272
Country, Fund and Time FE	Yes							

Table 5b. Investment focus, climate risks and fund-flow-performance relationship

	Panel A: Domestic funds				**Panel B:** International funds			
	All Funds	Low Risk	Average Risk	High Risk	All Funds	Low Risk	Average Risk	High Risk
PERF $_{(t-1)}$	0.625***	1.054	0.299	1.225**	0.150	0.517	-0.479	1.765
	(0.000)	(0.130)	(0.323)	(0.019)	(0.529)	(0.383)	(0.298)	(0.312)
Physical Risk (PRI)	-3.089***	-6.526***	-3.827***	-2.532**	-3.569***	-7.859***	-3.755***	-3.447*
	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)	(0.000)	(0.063)
PERF $_{(t-1)}$ x PRI	0.274***	0.771**	-0.014	0.531	0.409**	0.638	0.510*	0.249
	(0.000)	(0.012)	(0.944)	(0.107)	(0.010)	(0.139)	(0.072)	(0.724)
PERF-Squared $_{(t-1)}$	0.101***	0.655	0.261	-0.267	0.665***	-0.482	0.924***	-0.345
	(0.000)	(0.181)	(0.265)	(0.549)	(0.000)	(0.329)	(0.009)	(0.807)
Volatility $_{(t-1)}$	-0.053*	-0.214*	0.152***	-0.169**	-0.020	0.340*	0.051	-1.208***
	(0.056)	(0.077)	(0.008)	(0.016)	(0.730)	(0.057)	(0.629)	(0.000)
log (Assets) $_{(t-1)}$	-1.052***	-0.846**	-1.180***	-1.146***	-0.484***	-1.320***	-0.530***	-2.134***
	(0.000)	(0.037)	(0.000)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)
log (Fund Age) $_{(t-1)}$	1.803***	7.912***	3.635***	0.793	-1.118**	9.778***	-0.948	6.694**
	(0.000)	(0.000)	(0.000)	(0.589)	(0.043)	(0.000)	(0.308)	(0.022)
Size Beta $_{(t-1)}$	1.898***	2.301***	2.513***	2.822***	3.794***	7.395***	4.116***	6.822***
	(0.000)	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
MKT Beta $_{(t-1)}$	-1.036**	-3.388	-1.637*	-1.611	-4.831***	-10.383***	-5.530***	7.374*
	(0.029)	(0.105)	(0.077)	(0.388)	(0.000)	(0.000)	(0.000)	(0.072)
WML Beta $_{(t-1)}$	1.840***	1.857*	2.425***	2.568***	1.123***	0.961	1.656***	-0.166
	(0.000)	(0.062)	(0.000)	(0.001)	(0.004)	(0.478)	(0.009)	(0.943)
Intercept	-7.866***	-39.378***	-17.758***	-1.133	7.464***	-42.250***	6.861	-25.795*
	(0.000)	(0.000)	(0.000)	(0.890)	(0.008)	(0.000)	(0.167)	(0.057)
N	38,693	2,401	15,162	5,630	21,077	2,520	8,841	1,441
R-Squared	0.181	0.231	0.189	0.171	0.189	0.210	0.199	0.272
Country, Fund and Time FE	Yes							

Table 6. Mutual fund flows and performance – alternative specification

This table presents the results for Equation 5 based on the specification by Bollen (2007) and Renneboog, Horst and Zhang (2011). $Return_{i,[t-1,t-12]}$ is the average CH-4 alphas of fund i over the months t-1 to t-12; R^+ and R^- are indicator variables that equal one if the CH-4 alpha is non-negative or negative, respectively. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). All models include country and time fixed effects. Standard errors are double clustered by fund and time. The robust p-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

	All Funds	Low Risk	Average Risk	High Risk
Return x R+	1.559***	1.984***	1.740***	0.869
	(0.000)	(0.000)	(0.000)	(0.130)
Return x R-	0.082	-0.992*	0.126	1.458
	(0.564)	(0.075)	(0.902)	(0.175)
Volatility	0.013	-0.128	0.114*	-0.146*
	(0.685)	(0.190)	(0.073)	(0.070)
log (Assets) $_{(t-1)}$	0.107***	0.031	0.129***	0.120**
	(0.001)	(0.700)	(0.002)	(0.014)
log (Fund Age) $_{(t-1)}$	-1.026***	-1.208***	-1.020***	-1.403***
	(0.000)	(0.001)	(0.000)	(0.000)
Size Beta	0.045	0.439	0.153	-0.029
	(0.959)	(0.680)	(0.891)	(0.977)
MKT Beta	0.003	0.396	-0.510	3.704**
	(0.995)	(0.780)	(0.409)	(0.020)
WML Beta	1.319	-0.098	1.768*	1.236
	(0.132)	(0.911)	(0.087)	(0.365)
Intercept	3.489***	4.479**	3.243***	3.928***
	(0.000)	(0.030)	(0.000)	(0.006)
N	57,488	4,725	23,273	6,867
R-Squared	0.079	0.091	0.083	0.104
Country and Time FE			Yes	
Fund and Time Clustered SE			Yes	

Table 7. Climate risk and fund-flow-performance relationship – alternative specification

Panels A (B) present the results for Equation 6 that the tests the effect of transition (physical) climate risks and fund performance (in addition to several fund level controls) on monthly fund flows based on the alternative specification by Bollen (2007) and Renneboog. Climate risks (CRI) are captured by the transition risk index (TRI) (Panel A) and physical risk index (PRI) (Panel B) described in Section 2.2. Fund performance is measured by four-factor (CH-4) alphas. Fund flows are based on Franzoni and Schmalz (2017). The explanatory variables with subscript (t-1) are lagged by one month. $Return_{i,[t-1,t-12]}$ is the average CH-4 alphas of fund *i* over the months *t*-1 to *t*-12; R^+ and R^- are indicator variables that equal one if the CH-4 alpha is non-negative or negative, respectively. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). All models include country and time fixed effects. Standard errors are double clustered by fund and time. The robust p-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

	Panel A: Transitional climate risk index (**TRI**)				**Panel B:** Physical climate risk index (P**RI**)			
	All Funds	Low Risk	Average Risk	High Risk	All Funds	Low Risk	Average Risk	High Risk
Return x R^+	1.541***	1.725***	1.784***	0.924	1.544***	1.767***	1.695***	0.793
	(0.000)	(0.000)	(0.000)	(0.105)	(0.000)	(0.001)	(0.000)	(0.147)
Return x R^-	-0.084	-1.197**	-0.087	1.038	0.127	-1.025**	0.022	1.700
	(0.464)	(0.018)	(0.934)	(0.300)	(0.224)	(0.039)	(0.982)	(0.108)
Return x R^+ x **Climate Risk**	0.008	0.070**	-0.035	-0.049	-0.017	-0.269	-0.189	-0.275
	(0.491)	(0.037)	(0.125)	(0.308)	(0.876)	(0.464)	(0.294)	(0.397)
Return x R^- x **Climate Risk**	0.051***	0.045	0.107**	0.210**	0.298***	0.457	-0.679**	1.457**
	(0.000)	(0.243)	(0.024)	(0.043)	(0.000)	(0.172)	(0.040)	(0.037)
Volatility *(t-1)*	0.014	-0.122	0.112**	-0.148*	0.013	-0.119	0.115**	-0.148*
	(0.608)	(0.175)	(0.014)	(0.059)	(0.628)	(0.189)	(0.011)	(0.059)
log (Assets) *(t-1)*	0.107***	0.024	0.127***	0.121***	0.106***	0.028	0.128***	0.122***
	(0.000)	(0.745)	(0.000)	(0.010)	(0.000)	(0.708)	(0.000)	(0.010)
log (Fund Age) *(t-1)*	-1.024***	-1.192***	-1.018***	-1.392***	-1.024***	-1.205***	-1.016***	-1.391***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size Beta *(t-1)*	0.056	0.569	0.148	-0.033	0.047	0.616	0.158	-0.029
	(0.756)	(0.370)	(0.607)	(0.940)	(0.795)	(0.328)	(0.581)	(0.947)
MKT Beta *(t-1)*	0.009	0.504	-0.508	3.672**	0.004	0.436	-0.522	3.651**
	(0.981)	(0.729)	(0.357)	(0.017)	(0.991)	(0.768)	(0.343)	(0.017)
WML Beta *(t-1)*	1.294***	-0.275	1.765***	1.180	1.298***	-0.268	1.782***	1.182
	(0.000)	(0.694)	(0.000)	(0.122)	(0.000)	(0.703)	(0.000)	(0.123)
Intercept	3.513***	4.770**	3.352***	4.170**	3.526***	4.847**	3.338***	4.184**
	(0.000)	(0.014)	(0.000)	(0.011)	(0.000)	(0.013)	(0.000)	(0.011)
N	57,488	4,725	23,273	6,867	57,488	4,725	23,273	6,867
R-Squared	0.079	0.092	0.083	0.104	0.079	0.091	0.083	0.104
Country and Time FE	Yes							
Fund and Time Clustered SE	Yes							

Table 8a. Investment focus, climate risk (TRI) and fund-flow-performance relationship – alternative specification

Panels A and B present the results for Equation 6 that the tests the effect of climate risks and fund performance (in addition to several fund level controls) on monthly fund flows for domestic (international) focused funds, respectively. Climate risks are captured by the transition risk index (TRI) and physical risk index (PRI) described in Section 2.2. Tables 8a and 8b present the results based on transition (TRI) and physical (PRI) climate risk, respectively. Following Bollen (2007) and Renneboog, Horst and Zhang (2011), $Return_{i,[t-1,t-12]}$ is the average CH-4 alphas of fund i over the months t-1 to t-12; R^+ and R^- are indicator variables that equal one if the CH-4 alpha is non-negative or negative, respectively. The sustainability globe ratings represent funds in high risk (1), above average risk (2), average risk (3), below average risk (4) and low risk (5). All models include country and time fixed effects. Standard errors are double clustered by fund and time. The robust p-values are reported in parentheses. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All values are winsorized at 1% and 99%.

	Panel A: Domestic funds				**Panel B:** International funds			
	All Funds	Low Risk	Average Risk	High Risk	All Funds	Low Risk	Average Risk	High Risk
Return x R^+	1.373***	1.870***	1.546***	1.509**	2.577***	2.199**	2.633***	-1.810
	(0.000)	(0.004)	(0.000)	(0.026)	(0.000)	(0.017)	(0.000)	(0.141)
Return x R^-	0.066	-1.755**	1.900**	0.776	-2.108***	-2.512***	-2.473***	31.719***
	(0.587)	(0.035)	(0.029)	(0.441)	(0.000)	(0.005)	(0.000)	(0.002)
Return x R^+ x **TRI**	0.008	0.052	-0.025	-0.118**	0.036*	0.047	0.002	0.059
	(0.613)	(0.201)	(0.461)	(0.043)	(0.085)	(0.401)	(0.951)	(0.551)
Return x R^- x **TRI**	0.049***	0.026	0.123	0.238**	0.043	0.165**	0.112**	2.163*
	(0.000)	(0.678)	(0.103)	(0.023)	(0.190)	(0.010)	(0.031)	(0.053)
Volatility $_{(t-1)}$	-0.043	-0.309**	0.106	-0.186**	-0.050	0.310*	0.163	-1.511***
	(0.221)	(0.014)	(0.113)	(0.016)	(0.606)	(0.096)	(0.255)	(0.002)
log (Assets) $_{(t-1)}$	0.126***	0.220**	0.140***	0.119**	0.051	-0.102	0.076	0.196
	(0.000)	(0.037)	(0.000)	(0.012)	(0.259)	(0.308)	(0.192)	(0.189)
log (Fund Age) $_{(t-1)}$	-0.877***	-1.089***	-0.904***	-1.014***	-1.259***	-1.164**	-1.196***	-2.290***
	(0.000)	(0.004)	(0.000)	(0.001)	(0.000)	(0.028)	(0.000)	(0.001)
MKT Beta $_{(t-1)}$	0.036	0.793	0.329	-0.648	0.455	1.263	0.032	4.396**
	(0.856)	(0.344)	(0.307)	(0.159)	(0.375)	(0.342)	(0.966)	(0.012)
WML Beta $_{(t-1)}$	0.077	2.878**	-0.965	3.891***	0.627	-3.148	-0.359	11.875***
	(0.875)	(0.045)	(0.227)	(0.008)	(0.449)	(0.189)	(0.755)	(0.002)
Intercept	3.102***	2.017	3.619***	1.478	4.146***	6.811**	3.332**	10.722***
	(0.000)	(0.364)	(0.001)	(0.391)	(0.000)	(0.022)	(0.011)	(0.001)
N	37,595	2,342	14,844	5,584	19,893	2,383	8,429	1,283
R-Squared	0.086	0.126	0.083	0.104	0.074	0.087	0.089	0.123
Country, Fund and Time FE	Yes							
Fund and Time Clustered SE	Yes							

Table 8b. Investment focus, climate risk (PRI) and fund-flow-performance relationship – alternative specification

	Panel A: Domestic funds				**Panel B:** International funds			
	All Funds	Low Risk	Average Risk	High Risk	All Funds	Low Risk	Average Risk	High Risk
Return x R^+	1.382***	1.962***	1.457***	1.199*	2.620***	2.201**	2.646***	-1.839
	(0.000)	(0.004)	(0.000)	(0.072)	(0.000)	(0.014)	(0.000)	(0.161)
Return x R^-	0.277**	-1.705**	2.029**	1.495	-1.993***	-1.897**	-2.372***	30.095**
	(0.033)	(0.043)	(0.019)	(0.160)	(0.000)	(0.017)	(0.000)	(0.038)
Return x R^+ x **PRI**	0.024	0.116	-0.278	-0.979**	-0.278	-1.423*	0.062	-0.969
	(0.850)	(0.739)	(0.281)	(0.020)	(0.243)	(0.079)	(0.888)	(0.388)
Return x R^- x **PRI**	0.307***	0.310	-0.617	1.663**	0.223	1.425**	-1.001***	0.612
	(0.000)	(0.592)	(0.336)	(0.020)	(0.238)	(0.016)	(0.005)	(0.952)
Volatility $_{(t-1)}$	-0.044	-0.313**	0.111*	-0.185**	-0.050	0.304*	0.165	-1.452***
	(0.212)	(0.013)	(0.098)	(0.018)	(0.602)	(0.098)	(0.247)	(0.003)
log (Assets) $_{(t-1)}$	0.126***	0.221**	0.140***	0.118**	0.050	-0.101	0.077	0.197
	(0.000)	(0.036)	(0.000)	(0.013)	(0.267)	(0.313)	(0.191)	(0.197)
log (Fund Age) $_{(t-1)}$	-0.877***	-1.081***	-0.902***	-1.009***	-1.260***	-1.184**	-1.195***	-2.293***
	(0.000)	(0.004)	(0.000)	(0.001)	(0.000)	(0.026)	(0.000)	(0.001)
MKT Beta $_{(t-1)}$	0.029	0.771	0.340	-0.643	0.477	1.449	0.036	4.748***
	(0.884)	(0.356)	(0.291)	(0.161)	(0.349)	(0.257)	(0.961)	(0.006)
WML Beta $_{(t-1)}$	0.066	2.930*	-0.975	3.868***	0.641	-3.064	-0.373	11.673***
	(0.894)	(0.051)	(0.219)	(0.008)	(0.439)	(0.205)	(0.746)	(0.004)
Intercept	3.122***	1.939	3.590***	1.440	4.130***	6.869**	3.325**	10.647***
	(0.000)	(0.389)	(0.001)	(0.398)	(0.000)	(0.022)	(0.011)	(0.002)
N	37,595	2,342	14,844	5,584	19,893	2,383	8,429	1,283
R-Squared	0.086	0.125	0.083	0.104	0.074	0.087	0.089	0.120
Country, Fund and Time FE	Yes							
Fund and Time Clustered SE	Yes							

Table 9. Climate sensitivity and fund characteristics

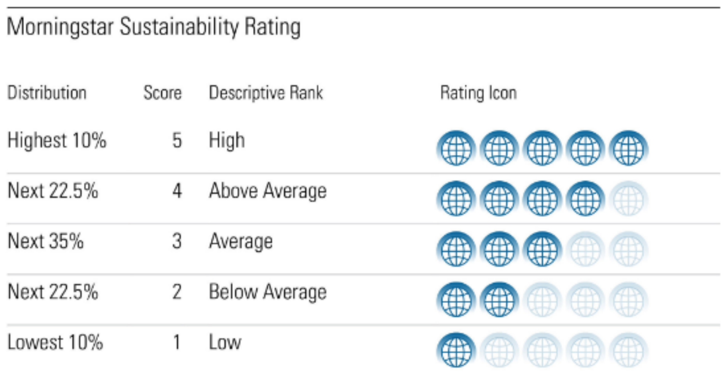
This table presents the descriptive statistics for funds sorted on the sensitivity of fund flows to climate uncertainty (i.e., climate beta) estimated via Equation 7. Funds in quintile 5 (1) represent funds whose flows are the most (least) sensitive to climate uncertainty, captured by their climate betas reported in the second column in each panel. Panels A and B report the results for funds sorted on their sensitivity to transition (TRI) and physical (TRI) climate uncertainty, respectively. Fund performance is measured by four-factor (CH-4) alphas and monthly fund flows are based on the flow measure of Franzoni and Schmalz (2017). Idiosyncratic volatility is computed relative to the benchmark Fama-French (1993) 5-factor model via rolling regressions as per Ang et al. (2006). Downside risk is measured by the Value at Risk values as per Ali et al. (2022a). Return Volatility is the time-series standard deviation of the fund's monthly returns over t-*1* to t-*11* months. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively

	Climate Beta	Raw returns	CH-4 alpha	Fund flow	Size (Mn)	Idiosyncratic Volatility	Downside Risk	Age (months)	Return Volatility
Panel A: Funds sorted on sensitivity to transition (TRI) climate risk									
Q1	-2.13	0.051	0.235	-2.254	139.631	2.775	-10.018	146.253	5.699
Q2	-0.614	0.253	0.262	-1.338	188.297	2.77	-10.321	190.902	5.864
Q3	-0.157	0.253	0.193	-2.793	253.263	2.476	-9.565	185.828	5.765
Q4	0.283	0.388	0.312	-1.505	221.411	2.334	-9.021	184.158	5.675
Q5	1.896	0.323	0.319	-0.021	134.783	2.455	-9.07	144.884	5.609
Q5-Q1	4.026**	0.272***	0.084***	2.233***	-4.848***	-0.32***	0.948***	-1.369**	-0.09***
t-stats	(2.10)	(4.44)	(14.19)	(23.42)	(-3.59)	(-31.92)	(27.76)	(-2.59)	(-3.02)
Panel B: Funds sorted on sensitivity to physical (PRI) climate risk									
Q1	-2.260	0.155	0.147	-1.806	135.540	2.476	-7.666	141.935	4.533
Q2	-0.482	0.377	0.180	-1.120	161.477	2.406	-7.935	186.633	4.623
Q3	-0.069	-0.559	-0.658	-8.887	164.290	2.167	-7.753	160.741	4.551
Q4	0.279	0.301	0.094	-2.847	176.719	2.114	-7.123	172.185	4.495
Q5	1.939	0.308	0.181	-0.734	158.308	2.238	-7.037	144.613	4.390
Q5-Q1	4.199***	0.153***	0.034***	1.072***	22.768**	-0.238***	0.629***	2.678**	-0.143***
t-stats	(3.4)	(5.36)	(12.16)	(21.06)	(1.92)	(-42.11)	(32.75)	(2.14)	(-8.72)

APPENDIX.

Figure A1. Globe rating on Morningstar website.

This figure provides the mapping of the sustainability (ESG) ratings with the rating description and rating icon (Globe) as published on the Morningstar's website.[11]



Morningstar Sustainability Rating

Distribution	Score	Descriptive Rank	Rating Icon
Highest 10%	5	High	
Next 22.5%	4	Above Average	
Next 35%	3	Average	
Next 22.5%	2	Below Average	
Lowest 10%	1	Low	

[11] A fund with high (low) ESG risk relative to its Morningstar Global Category would receive 1 (5) globe. The details of the ratings can be found here: https://www.morningstar.com/articles/957266/the-morningstar-sustainability-rating-explained

Table A1. Descriptive statistics of mutual funds

Panels D and E present the summary statistics of the mutual fund characteristics for domestic and international funds, respectively. Panel F presents the pair-wise correlations among the variables used in Panel A. We classify the funds into international and domestic based on the fund investment category from Morningstar. Fund performance is measured by four-factor (CH-4) alphas. Fund flows are based on Franzoni and Schmalz (2017). Fund Size is log(assets). Fund Age is the total number of months in fund's existence. Idiosyncratic volatility is computed relative to the benchmark Fama-French (2015) 5-factor model via rolling regressions as per Ang et al. (2016). Size, MKT and WML betas are coefficients obtained through 36- month rolling regressions of Fama-French (2015) 5-factor model on raw fund returns that capture the fund investment styles tilted towards size, market and momentum portfolios respectively. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. All the values are winsorized at 1% and 99%.

Panel D: Domestic funds							
	Mean	Std. Dev.	Min.	p25	Median	p75	Max.
$FLOW$	-0.894***	5.589	-20.986	-1.702	-0.455	0.355	16.1
CH-4 Alpha	0.265***	0.469	-0.652	0.004	0.252	0.534	1.276
Raw returns	0.56***	7.494	-24.71	-2.69	1.06	4.93	18.64
Volatility	6.302***	3.053	2.416	4.062	5.38	7.885	15.466
Fund Size	2.957***	2.38	-2.848	1.316	3.067	4.73	7.488
Fund Age (Months)	5.087***	0.573	3.497	4.82	5.182	5.472	6.057
Idiosyncratic Volatility	2.668***	1.081	1.136	1.889	2.395	3.143	5.431
Size Beta	-0.045***	0.265	-0.697	-0.201	-0.054	0.11	0.628
MKT Beta	0.9***	0.129	0.537	0.839	0.91	0.974	1.207
WML Beta	-0.049***	0.203	-0.467	-0.189	-0.057	0.076	0.473
Panel E: International funds							
	Mean	Std. Dev.	Min.	p25	Median	p75	Max.
$FLOW$	-0.617***	6.36	-20.986	-1.667	-0.194	0.794	20.174
CH-4 Alpha	0.475***	0.365	-0.58	0.278	0.498	0.705	1.209
Raw returns	0.495***	6.126	-14.93	-3.31	1.2	4.345	15.33
Volatility	5.261***	1.856	2.346	3.932	4.884	6.339	10.937
Fund Size	3.173***	2.471	-2.636	1.355	3.434	5.076	8.374
Fund Age (Months)	4.88***	0.631	3.434	4.431	5.011	5.375	5.984
Idiosyncratic Volatility	2.727***	1.076	1.248	1.955	2.446	3.187	5.647
Size Beta	0.032***	0.216	-0.569	-0.086	0.034	0.158	0.51
MKT Beta	0.853***	0.169	0.494	0.757	0.831	0.938	1.293
WML Beta	-0.207***	0.184	-0.602	-0.336	-0.199	-0.093	0.258

Panel F: Pair-wise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) $FLOW$	1.000									
(2) CH-4 Alpha	0.069***	1.000								
(3) Raw returns	0.000	-0.057***	1.000							
(4) Volatility	-0.071***	-0.102***	0.300***	1.000						
(5) Fund Size	0.048***	0.215***	-0.015***	-0.049***	1.000					
(6) Fund Age	-0.128***	-0.053***	0.008*	0.068***	0.071***	1.000				
(7) Idiosyncratic Volatility	-0.094***	-0.157***	0.055***	0.220***	-0.024***	-0.012***	1.000			
(8) Size Beta	0.035***	0.206***	0.002	-0.057***	0.010**	-0.070***	-0.151***	1.000		
(9) MKT Beta	-0.017***	0.116***	0.002	0.249***	-0.019***	0.112***	0.000	0.205***	1.000	
(10) WML Beta	0.054***	-0.254***	-0.008**	-0.008*	-0.038***	0.000	-0.354***	-0.111***	-0.084***	1.000

Table A2. AR (1) estimates of physical and transition climate risk concern

This table presents the estimates of monthly autoregressive process of order 1 concern time series on physical risk (Equation 1a) and transition risk (Equation 1b) for the period Jan 2018-Dec 2022. Standard errors are shown in parenthesis.

	$Concern_{t,PR} x100$	$Concern_{t,TR} x100$
Drift c	7.01	9.02
	(0.21)	(0.24)
ϕ	0.51	0.58
	(0.11)	(0.11)

Table A3. Transition climate risk top news articles

This table reports the dates, the Transition Risk Index in percentage (TRI %), the main news topics, and lists of relevant article's title/extracts for the ten days with highest transition risk over the period Jan 2018-Dec 2022. News sourced from The Australian and The New Zealand Herald *Reuters News* with an Asia-Pacific regional focus. "CC" acronym for "climate change".

Date	TRI %	Transition risk news topics	Transition risk relevant news titles/[extracts]
08/12/2022	13.19	Renewable energies, wind, solar, green hydrogen, natural gas; Energy transition; Domestic solar manufacturing industry to meet AUS 43% emissions reductions by 2030 and net-0 by 2050; Costly transition; Nuclear power; AUS National environment protection agency; Plibersek reforms; Environment laws; Nature Repair Market Regulation	Forrest the biggest green player after $4bn-plus CWP buy; Solar manufacturing industry essential, says CSIRO; Highbury helps Forrest land $4bn CWP deal; Nuclear should remain a key option in energy debate; Finally, laws with teeth to reverse decline of nature
20/05/2020	12.34	Mitigation actions - AUS $2bn for emission reduction technologies; Techn. change in heavy industry and transport; New AUS standards for solar panels; NZ renew. energy for a green data centre industry	Climate still a battleground as ALP goes on attack; [NZ's high renewable energy base can rocket us to forefront as world shifts to greener, more tech-based ways of working in 21st century]; Power must 'switch on' energy reform; Solar panel shake-up to offer clarity on supply
06/08/2020	11.01	Low emission technologies; Renewable energies; Solar and wind energies; CCS; Hydrogen; Environmental regulation; Government sustainability issues pressures	Slump smudges clean energy fund; [Environmental regulations]
06/06/2022	10.54	Energy mix, hydrogen, natural gas; AUS potential key hydrogen supplier to Asia and Europe, $185bn in renew. /hydrogen projects; AUS gov. energy mix challenges; CCS; Coal-fired power plants closure - job losses; Dispatchable techn.; CC increases energy costs; Investors and fossil fuel divestment; AUS needs a Germany–like "just transition" principle to ensure an orderly transition	Energy users pre-empting policy on hydrogen: GE; Eastern {Australian} states have gas they just need the will to extract it; The rise of woke capitalism harms national interest; Why natural gas is critical for energy security; Labor's race for answers as energy crisis bites; Power workers didn't need a tech guru to show it's crunch time
02/11/2018	10.07	Ocean waves into clean electricity; AUS potential leader in wave energy technology; Faster warming oceans warns nations - urgent CO2 emissions reduction and CC mitigation, reduce carbon budget; Techn. advances, Argo floats, CCS; World's largest solar thermal plant in AUS at risk	Momentum swells for wave energy; Ocean study's climate change warning; BHP won't stop mining coal; Row taints review of solar plant
10/09/2020	9.36	Renew. energies; Techn. for decarbonisation; Climate risk analysis for business decisions; CC and transition in the beef industry, CO2 sequestration and offset; Carbon-conscious consumer; AUS water reform	BHP executives face carbon test; Study to beef up carbon-neutral credentials; Water reforms a win for farmers and improved use
31/01/2019	8.74	OECD calls AUS greater efforts on meeting Paris Agreement climate targets and GHG emissions reduction, biodiversity protection, and chemical handling; Need long-term low carbon strategy	Mixed review from OECD as our biodiversity worsens
24/08/2021	8.60	Hydrogen energy, AUS hydrogen hub development, potential exports to Japan; Carbon emissions reduction; NZ gov. concerned on energy transition; Fuel Security	Rio in deal with Sumitomo for Qld hydrogen hub; Strategic logic fuels the race for scale in Z Energy takeover
23/03/2018	8.56	Turnbull gov. concerned about proposed closure of coal-fired power station as renew. energies cannot ensure dispachable electricity in AUS, whereas gas, hydro, pumped-hydro, biomass and batteries do; Clean energy technology; Energy policy	Liddell is a loss, but energy guarantee would light the way forward
11/02/2021	8.55	Net-0 targets; Renew. energy projects Western AUS, pollution cuts, Fuel security fears; Hydrogen/nuclear power; AUS adaptation water management in a changing climate	Thinking about our planet in the wake of pandemic; State Libs to close coal-fired plants; Fuel security fears as Altona closes; Emergency water plan on table

Table A4. Physical climate risk top news articles

This table reports the dates, the Physical Risk Index in percentage (PRI %), the main news topics, and lists of relevant article's title/extracts for the ten days with highest physical risk over the period Jan 2018-Dec 2022. News sourced from *Reuters News* with an Asia-Pacific regional focus. "CC" acronym for "climate change".

Date	PRI %	Physical risk news topics	Physical risk relevant news titles/[extracts]
20/05/2020	10.91	AUS Bushfires and Droughts - lost economic opportunities; NZ Droughts Auckland, failure to adapt, resources mismanagement, water restrictions, driest start to the year on record	[Drought-stricken Auckland]; Water storage falls, outlook bleak; [Recent bushfires and droughts loss of economic opportunities]
27/02/2018	8.68	NZ warmest summer in 150 years, heatwaves, droughts, floods, shrinking of glaciers, huge deluges, cyclones; Changing ocean temperatures and wind speed; Animal extinction and migration; Biodiversity loss; sea level rise, global warming; Climate and biodiversity protection actions needed; NZ involvement with international organizations and NZ National Plan of Action	[… warmest summer in 150 years. It has been quite remarkable really, being 2C above average with heatwaves, droughts and floods. Our glaciers shrank yet again with the heat.]; Rare albatross in rapid decline
02/06/2020	8.16	Biodiversity loss; Rivers, lakes, and estuaries degradation; NZ gov. environm. policy for freshwater ecosystem; A one in 100-year storm, landslips, floods in Coromandel, NZ; Changing ocean conditions affect marine ecosystem, blue whales at risk; Marine heatwaves; Climate adaptation, resiliency and infrastructural changes needed; Food security	Clean river promises have been swept away; Coromandel farmers to wake to slips; How NZ's blue whales stay cool and get their krill
17/01/2022	8.01	Underwater volcano Hunga Tonga eruption, tsunami, floods; Cyclone Cody; Gales, swells, sea surges, coastal inundation; NZ mln dollars damage; Rising sea levels, vulnerability of low-lying areas; Impact of warming temperatures and extreme weather events (droughts, frost, hailstorms, bushfires) on agriculture, relocation costs; Need for government CC action; CC impact on food prices; Need for management strategies for bushfires	Cool change a hot topic for wineries; Family fears for island home from Tonga swell; Brutal surges sink 12 boats, smash marina; {Cyclone} Cody skirts New Zealand
08/03/2018	7.27	Tropical cyclone Hola NZ; CC impacts NZ native species, habitat destruction; Extreme weather, storms, cyclones, swells, king tides, massive waves; Hot weather, and rising sea level; Beaches erosion; Human health risks; Climate adaptation; Ocean drift patterns; Climate models	Cyclone looms Tropical Cyclone Hola is lying in wait just to the east of Vanuatu; Summer storms sweep away a generation of little blue penguins; Chilling fact is most climate change theories are wrong; 'World's oldest message in a bottle' surfaces after 132 years
24/06/2021	6.44	Great Barrier Reef affected by CC; Biodiversity loss; AUS gov. environm. Adaptation, China denies "in danger" classification	China hits back over {Great Barrier} reef 'smear'
07/07/2020	6.02	NZ water scarcity; NZ CC concerns and pollution/plastic waste disposal effects on oceans and marine wildlife	Park irrigation 'beyond stupid'; 5 ugly facts With Plastic Free July under way, Herald science reporter Jamie Morton looks at five figures that reveal the alarming enormity of NZ's plastic problem — and five things we can do about it [growing concerns about plastic pollution and climate change]
23/11/2022	5.94	Longer bushfire seasons, droughts, rising sea and air temperatures; Heat extremes, decline in rainfall, sea levels rise, floods/damage to coastal areas; AUS gov adaptation, environ. protection; River systems; Scarce water savings in the Murray Darling Basin; CC disrupts food supply chain in AUS; Food security	Future shock: more heat, more bushfires, more droughts; Why we will oppose reforms to the RMA; Up the creek on Murray-Darling water targets; Plan needed to keep shelves full
06/12/2021	5.90	Heatwaves, floods, fire danger, thunderstorms; Impact of La Nina on AUS weather patterns, rivers flood risk; Environment protection from increased bushfires risk; Declining natural resources, volatile climate, sustainable innovation in the food/agriculture industry	Heatwaves hit west as floods swamp east; Plant-based meat can feed and protect planet
01/04/2022	5.79	Bureau of Meteorology's failure to predict extreme weather events that caused flood disasters in NSW and Queensland; Rising temperatures; AUS avoided deforestation; Savannah burning; Biodiversity loss	Under-fire weather bureau 'has been failed on funding'; Big project developers back carbon market review