Climate Disaster-Triggered Attention Shifts: Evidence from Green Mutual Fund Flows

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Master Thesis in Finance, Spring 2022

Stockholm School of Economics

ABSTRACT

This thesis empirically investigates the degree to which climate disasters have a behavioral impact on mutual fund flows into green versus non-green funds. Through a twofold analysis that studies both Google search volume-proxied investor attention as well as green and control mutual fund flows, we show that local climate disasters have a positive impact on both investor attention and behavior towards green funds. Thus, even though climate change is a gradual process, its investor awareness happens rather in shocks. These findings follow from the May 2018 to December 2021 period, wherein we identify green funds through the Morningstar Low Carbon Designation. Beyond that, we find this effect to hold for up to three months, and we show that the effect is stronger for local disasters than for larger foreign disasters, the latter playing into the salience explanation. In line with prior studies' findings, our paper adds to literature on climate-related investment behavior and can be of value to investors and equity analysts.

Keywords: Climate disasters, Climate change, Mutual funds, Behavioral finance, LCD

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§ We would like to sincerely thank Anders Anderson for his valuable feedback and insights in the writing process.

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1 Introduction

The ‘Frog in the pan’ hypothesis builds on the phenomenon that a frog exposed to gradually heating water ultimately sits and boils, while a frog suddenly exposed to boiling water would jump out. As per Da et al. (2014), this holds also for investors, being more attentive to sudden events. Climate change can too be compared to this hypothesis, as indicated by Choi et al. (2020). Being a long-term gradual process, climate change is not substantially visible on a personal level. Natural disasters in turn do act as sudden and attention-grabbing events, although only showing marginal information on climate change severity and not acting as drivers or impacting climate change fundamentals in themselves. With the last seven years having been the warmest years on record, as per the WMO (2022), this has gone hand-in-hand with an increased number of these extreme weather events, including heatwaves, exceptional rainfall, floodings, and droughts. News outlets have subsequently tied the occurrence of such events to the presence of climate change on multiple occasions[1], adding to the reach and awareness of climate change. Among the many implications, for investors this includes changing returns on especially carbon-intensive businesses and industries, which are likely to face restrictions in productivity and thus economic output (Nordea, 2021). While it may be logical to assume that professional investors have regular discussions on the implications of gradual climate change, this might not be true for less-sophisticated retail investors, who need ‘sudden boiling water’-type triggers to react.

Therefore, we set out to examine the triggers and investment behavior of predominantly retail investors in light of climate change developments. As found by Fang and Peress (2009), topics covered by mass media can reach enormous amounts of people, thereby having an impact on the investment behavior of amongst others retail investors. Given the recent attention by mass media to the link between severe weather events and climate change, the occurrence of these climate disasters can be seen as one of the factors that draw people’s attention to climate change. Building upon this effect, our focus on investor behavior leads us to study direct cash flows by those investors. Paired with this, Barreda-Tarrazona et al. (2011) reported on their finding that investors allocate substantially more money to funds where they see higher diversification and where they are significantly informed about their sustainability focus. Accordingly, any behavioral trigger could see more apparent and direct investment changes

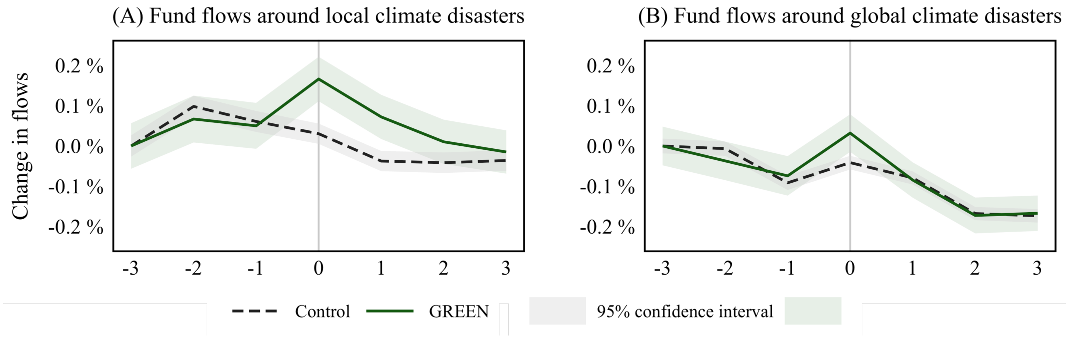
[1] See for instance the news articles by The New York Times (Fountain, 2019), The Guardian (Carrington, 2019) and BBC (McGrath, 2021).

within labeled mutual funds than in stocks or indices, as for the latter two, investors' own research may still be required to find information on for instance carbon exposure levels. Therefore, our study analyzes the extent to which climate disasters generate investor attention, as well as to which extent these events subsequently impact low carbon designated mutual fund flows. Additionally, we recognize and take into account the broad range of prior research on the implications of information salience, all the way back to e.g. the impactful work by Kahneman and Tversky (1973), indicating that the vividness or proximity of events influences how people may perceive their consequences. As such, we extend our study to include analyses of the difference between climate disasters that happened within the investor's home country, and those disasters that happened internationally.

Figure I below visualizes the main findings of our thesis. It illustrates how according to our analyses, investors allocate more money to green mutual funds at times of climate disasters, relative to non-green-labeled funds. As per Model (A), for local disasters this difference amounts to 14 basis points compared to the base month, which totals on aggregate \$5.3bn more flows to green funds than to control funds, per climate disaster. Moreover, our results indicate that this difference is significant at times of same-country climate disasters, while being insignificant during large global (yet foreign) climate disasters. Given that the largest climate disasters globally hold considerably more weight towards the extent and effects of climate change, the finding that these events form less of a trigger than smaller but local events plays into the salience explanation. As implied by our results, investors value events in their close proximity observably more when making investment decisions. We furthermore find that these results are in line with heightened investor attention towards climate change following such natural disasters. Interestingly, our results show only a direct shock from climate disasters to fund flows, while finding no relation between Google search volume, as a measure of attention, and those same fund flows. This could be an indication that the group of people who search for climate change on Google, does not match the group of people who invest in mutual funds. Thus, similar to Anderson and Robinson (2021), implying that there is a disconnection between the awareness of climate change and potential green investment preferences, and the financial literacy to act on this information. Lastly, our analyses show that the shock towards green funds can hold for up to three months after initial awareness of the disasters, partially as certain events span consecutive months, while also showing some lagged effect of climate disasters on investment decisions.

Figure I: Fund Flows at Times of Climate Disasters

This figure shows the mean change in flow, by month, for the seven-month period around the first occurance of a climate disaster. Model (A) considers the fund flows at times of a local climate disaster within a fund's region of sale, with Model (B) considering global disasters beyond a fund's region of sale. Flows are aggregated across all funds over the May 2018 - December 2021 period, inclusive. The considered fund flows are segmented by GREEN, those with the LCD label, and control funds. Change in flows is indexed to base month t-3, with the consecutive values showing non-cumulative point estimates. The considered climate disasters correspond to those specified in Table I.



These results and our developed analyses build upon prior literature in adjacent fields. Research on both investor attention and mutual fund flows is extensive, covering a wide range of topics at their intersection, including ample studies with a sustainability angle. Past investor attention studies have analyzed amongst others the public awareness of climate terminology and the link between investor attention and mutual fund flows (Lineman et al., 2015; Chen et al., 2021), for the latter finding supportive results as well as denoting the less-sophisticated characteristics of those investors. Connecting with climate disasters, prior studies have found that those disasters with clear global warming links, as well as clear abnormal weather events, are most likely to have an attention-grabbing effect (Sisco et al., 2017). Furthermore, recent papers by El Ouadghiri et al. (2021) and Marshall et al. (2021) provided initial views on the effects of climate disasters, researching sustainable stock indices and local-domiciled mutual funds in the US respectively. Lastly, Bernile et al. (2021) found further significance of the salience of local climate disasters to the performance of US mutual fund managers.

Given this research environment, our paper adds to literature in multiple ways. First, the field of climate disasters and their behavioral impact on financial investments remains novel, with results still varying. For instance, the prior mentioned paper by Marshall et al. (2021) reported a positive effect on fund flows of as high as 40% in disaster months, whereas Kollias and Papadamou (2016) reported insignificant results altogether. Therein, our findings provide a new building block towards conclusive results. Second, mutual fund research which included climate disasters thus far primarily focused on local impacts (e.g. Alok et al. (2020)), thereby leaving large international disasters with further-reaching consequences out of scope. Our study considers both. Third, from the limited number of papers that do study the effect of climate disasters on investment objects, to the best of our knowledge, none of these consider the difference between local and international events to affirm the importance of event salience in the relationship, which our paper does. Last, current literature is often exclusively focused on US-based funds. Even though it can be assumed that results in Europe or elsewhere are in line with those in the US, we argue that given the differing opinions on climate change between geographies (Shwom et al., 2015), a study that goes beyond the US is of added value. More so, with only a minor share of current literature considering non-US geographies (Karolyi, 2016), we add to literature by testing current beliefs, exhibiting whether results are indeed in line with US-based findings. With all the above, we provide findings that are of added value to investors in both professional and retail settings.

Within our thesis, we have particular attention towards two splits, concerning mutual funds and climate disasters. For the scope of our paper, we will refer to green funds whenever we analyze those funds that hold the Low Carbon Designation ('LCD') label. Our study oftentimes compares green funds with control funds, those without the LCD label, to study the extent to which flows between those two segments differ. Additionally, within the thesis we will refer to both local and global climate disasters. In our paper, this refers to respectively those natural disasters that took place only within the country of analysis ('locally'), or to those disasters that took place anywhere beyond the country of analysis ('globally').

The remainder of our paper is structured as follows. Section 2 covers the empirical setting, which includes an analysis of the current literature environment on investor attention, climate change and related investment triggers, as well as mutual fund flows. This is followed by the hypothesis development, which builds upon the existing literature. Next, Section 3 concerns the data, outlining both the rationale behind the included data, the gathering process and descriptive statistics. Subsequently we present our empirical results in Section 4. Here, we cover the analyses' methodology and results, testing the hypotheses and covering the implications of our findings. After that, we also include robustness tests, before lastly presenting our conclusion in Section 5.

2 Empirical setting

2.1 Literature review

Investor attention

Investor attention and its links to financial markets' cash flows, price developments and trading volumes, have been the topics of interest in behavioral finance literature before. Studies are widespread, analyzing as well as finding supportive results for the effect of investor attention towards e.g. stock prices (Da et al., 2011; Mbanga et al., 2019), commodity prices (Han et al., 2017; Rao and Srivastava, 2013) as well as mutual fund flows (Marshall et al., 2021; Hartzmark and Sussman, 2019). Within investor attention-focused studies, there are a variety of methodologies used to measure attention. Some of its earlier determinants remain somewhat ambiguous, thereby providing a challenge from a measurement point of view (Li et al., 2019). These measures historically included a number of indirect empirical proxies such as firm sizes, extreme returns, trading volume and news headlines (Barber and Odean, 2008). More recent are the use and introduction of direct measures such as the Google search volume index ('GSVI'), as introduced by Da et al. (2011), Twitter sentiment measures (e.g. by Rao and Srivastava (2013)), as well as for instance topic-specific measures such as the use of SEC's EDGAR Log files by Li et al. (2019). These are revealed attention measures, implying that their input (e.g. a search on Google) undoubtedly happens with someone's attention, therefore providing a direct and unambiguous measure (Da et al., 2011).

GSVI is found to be most appropriate within mutual fund flow research due to this unambiguity, as well as for two more reasons. First, the usage and by extension the credibility of this measure relates to the objects of interest within the study. Prior research into the characteristics of mutual fund investors has shown that their financial literacy lacks that of sophisticated professional investors (Alexander et al., 1998). This differentiates research on the attention of retail investors from institutional investors, with the latter using for instance Bloomberg terminals and as such have a much slimmer direct link to Google search data (Li et al., 2019). Second, as also initially reported by Da et al. (2011), is the fact that Google continues to be the dominant search engine, meaning that their reported search volume is highly representative of the general population's internet search volume. This last reason has only become more prominent over time. Da et al. (2011) stated a 72% Google market share in all internet searches within the United States, a percentage which has grown to 88% as of February 2022, and even higher worldwide, at 92%[2].

As a consequence, ample recent literature that links investor attention to either mutual fund flows, or to sustainability and climate change, falls back upon GSVI data and its Da et al. (2011)-proposed methodology. Within climate change-focused theses, research by amongst others Lineman et al. (2015), Anderegg and Goldsmith (2014) and Choi et al. (2020) covered GSVI data, having found supportive results for respectively the public awareness on climate terminology as well as increased attention to climate change through news-covered events and unusually warm weather. Next to that, mutual fund literature has previously linked GSVI-measured attention data to fund flows in papers by e.g. Chen et al. (2021) and Da et al. (2015), therein finding supportive evidence both consistent with the attention-grabbing purchase hypothesis, as well as with showing predictive sentiment-based results out of equity funds and into bond funds.

Climate disasters' effect on investor attention

Climate change has increasingly been changing investors' minds, having come a long way from the early-2000s majority that opposed climate-related resolutions, as found by a Ceres report (Baue and Cook, 2008). This rising trend in attention to climate change corresponds with people's overall awareness of climate change, as measured by media attention. Both Boykoff and Boykoff (2007), and more completely Schmidt et al. (2013), have found and aggregated an abundant amount of empirical evidence showing the increase in climate-related media coverage globally. Studies by amongst others Klibanoff et al. (1998) as well as Choi et al. (2020) then further use media coverage as proxy for investor attention. Klibanoff et al. (1998) stated and found support for the salience of front-page news to cause investors' responses, however temporarily, with an increased focus towards fundamentals. This broadly researched concept of information salience in turn serves as an important determinant within the existing literature on event-triggers for the attention towards climate change (e.g. in Ghosh and Zhang (2021); Alok et al. (2020)).

[2] Source: StatCounter Global Stats, accessed March 2022 (https://gs.statcounter.com/search-engine-market-share).

As explored by Lee et al. (2015), there are a number of determinants playing a role in people's climate change awareness and risk perception. Therein, awareness varies between countries and is influenced by certain fundamental factors, such as level of education, as well as by factors such as the vulnerability to climate-related hazards, wherein the frequency of extreme weather events plays a role. Additionally, Mavrodieva et al. (2019) doubled down on the role of social media, analyzing the effect of salient news events on public awareness. Their results found a considerable climate-awareness impact from climate activist events, climate conferences, summits, as well as from e.g. highly viewed movies and documentaries. This corresponds with findings by e.g. Boykoff and Boykoff (2007) and Grundmann and Scott (2014), with the latter also finding a similar attention-spike from Hurricane Katrina.

Apart from Hurricane Katrina, being in the top-5 deadliest hurricanes in the US with over $100bn in approximated damages (NWS, 2016), there is more precedent research that highlights the attention-drawing effects of climate events (Sisco et al., 2017; Huynh and Xia, 2021; Han et al., 2020). Herein, e.g. Sisco et al. (2017) found that particularly those events that are clearly linked to global warming, those standing out as abnormal weather events and those in people's close proximity, draw significant attention to climate change. Consequently, studies have been published that use investors' shifted attention following a climate disaster, to subsequently explore its effect on investment decisions. Herein, stock-related studies range from the impact of climate disasters on returns, on portfolio allocation as well as on for instance insider trading (El Ouadghiri et al., 2021; Ghosh and Zhang, 2021; Ma et al., 2022). Furthermore, existing mutual fund research covers the reallocation of holdings as well as the flows into sustainable-labelled funds as a result of certain climate disasters (Alok et al., 2020; Marshall et al., 2021).

Mutual fund flow determinants and the role of climate events

As of Q4 2021, worldwide regulated open-ended funds totaled $71tn in total assets, being an aggregate of all long-term (e.g. equity, bond and balanced) and money market funds (Investment Company Institute, 2022). In the same quarter, the net cash inflow for all these funds globally was $1.1tn. To get a grasp of that size, equity funds accounted for $34tn (47%) of all mutual funds assets, meaning roughly one-fourth of the global market capitalization ($116tn as of Q2 2021) was kept by mutual funds (World Federation of Exchanges, 2021). Herein, the number and size of sustainable funds has surged amidst the continuing pivot towards sustainability. According to UNCTAD (2021), based on Morningstar data, worldwide sustainable funds totaled $1.7tn in 2020, or 3% of all open-ended funds at the time, having quadrupled in size since 2016.

As such, mutual funds and their deemed sustainability have a major global financial impact, naturally attracting vast amounts of research. Within this pile of literature, ample studies have been done on performance (Kumar et al., 2016; Dolvin et al., 2019) and fund flows, notably by Hartzmark and Sussman (2019) as well as Ammann et al. (2019), of sustainable funds. The latter two both found consistent evidence that the Morningstar sustainability rating, as depicted by the simple and salient globe ranking, has a positive effect on flows for high-rated funds as well as vice versa. These papers cover investment decision determinants that do not cover investment object fundamentals. Next to this, a deeper look into existing research shows that fundamental determinants for sustainable funds' flows relate to past performance (Capon et al., 1996), current ownership and switching costs (Benson and Humphrey, 2008), as well as sustainable finance literacy (Filippini et al., 2021).

As covered previously, climate disasters, potentially being physical examples and the consequences of climate change, can form as a trigger for climate change awareness. Within the scope of climate disasters as a behavioral trigger for fund flows, existing literature is seemingly novel and remains scarce. Marshall et al. (2021) analyzed and found evidence for the higher inflow of capital into mutual funds with an environmental focus by investors who paid attention to socially responsible investing, after county-level natural disasters in the US. Fiordelisi et al. (2020) found support showing that the outperformance of SRI-strategy funds coincided with months of relatively high climate disaster activity. Additionally, Bernile et al. (2021) analyzed the behavioral effect of US-located disasters on the volatility of US-managed mutual funds that invest outside the US. Their study, while more focused on the extent of being personally affected, found support that return volatility decreased for the first years after a climate disaster took place. From a fund management perspective, Alok et al. (2020) found empirical support for the underweighting of disaster zone stocks by managers within disaster regions. In their paper, which is overall focused on portfolio allocation and disaster risk, they found this to be related to a decreasing salience bias over time.

Within the beforementioned literature, different scopes are covered in terms of research focus, geographies and fund selections, as such having different results in the end with respect to the influence of climate disasters. Notwithstanding, it is interesting to note some differences in magnitude. Marshall et al.'s (2021) results show a statistically significant difference of as high as 40% between the flows of sustainable and control funds in a month with a climate disaster. Compared to the earlier-mentioned paper of El Ouadghiri et al. (2021), who found barely positive results, it can be noted that not all findings are aligned. Even though both analyzing stock indices, El Ouadghiri et al. (2021) further referred to Kollias and Papadamou (2016) who found insignificant effects altogether, further emphasizing this inconsistency. Thereby, it is apparent that the latter two focus on the largest five and three climate disasters per continent respectively, whereas Marshall et al. included all events >$1m in damages for US states. As such, the differing results could be partially explained by the salience explanation, as touched upon by e.g. Alok et al. (2020) and Bernile et al. (2021). While also deviating in terms of research focuses, they both resemble Marshall et al. (2021) in that they include events based on significant local damage in relation to the state/county of occurrence, seemingly signaling the relation would be weaker for extreme weather events in another geographic area.

Gap in currently existing literature

In all the above it becomes apparent that literature on particularly investor attention, sustainable fund performances and to an extent sustainable fund flows is already extensive. After a deep dive into fund flow research for sustainable mutual funds, including in particular the coverage of climate disasters as investment determinants, we find that to the best of our knowledge research in this area remains scarce and inconclusive. Specifically, the inconsistent findings on the significance of a climate disaster's effect, as well as the incomplete conclusions on the importance of local event salience, leaves ample room for additional research.

Given this, we have identified the need for a study on the effect of climate disasters on investor behavior within mutual funds, both on a local-country level, as well as on a global level. According to Karolyi (2016), only 16% of the studies in the top four Finance journals examine non-US markets. Moreover, since public opinion on climate change does differ considerably between geographies, both in terms of concern as well as in terms of support for policies (Shwom et al., 2015), we see considerable added value in including non-US data in our study. Our paper adds further valuable insights by including GSVI-measured attention data to measure the extent to which search volume coincides with climate disasters, to further quantify the significance of event salience to investor behavior within the scope of climate events.

2.2 Hypotheses

Building upon the literature environment, historical findings give us good indications of what we could expect from our envisioned analyses. Research by Anderegg and Goldsmith (2014) studied the attention-grabbing effect of climate media coverage, finding significant attention spikes. Next to that, Choi et al. (2020) looked at the direct climate phenomenon of global warming, finding significantly more GSVI-proxied investor attention in abnormally warm weather. Moreover, prior literature already found partially supportive evidence that climate disasters increase investor attention (Schäfer et al., 2014; Sisco et al., 2017). As such, our attention-focused hypothesis is as follows:

H1: Local climate disasters increase same-country investor attention to climate change

Subsequent to our attention hypothesis, a second hypothesis can be formed that focuses on mutual fund flows. El Ouadghiri et al. (2021) found supportive evidence for increased returns of sustainable stock indices following climate disasters. Marshall et al. (2021) researched the impact of local county-level weather events in US states. Their findings showed supportive evidence for both the attention-grabbing effect and abnormally higher flows into green funds, with the latter referring to flows into green funds that are significantly higher than into control funds. As such, we hypothesize:

H2: Local climate disasters abnormally increase same-country targeted green mutual fund flows through increased climate change awareness

As found by Klibanoff et al. (1998), fund prices of closed-end country funds are significantly sensitive to salient news, as investors are found to then react more to fundamentals. Bernile et al. (2021) found that the investment behavior of professional investors changed significantly after being personally subject to natural disasters, compared to this not being the case for investors in non-disaster countries. As such, we hypothesize in extension to both the attention-focused hypothesis and the fund flow hypothesis, that the effects are stronger when considering local climate disasters:

> **H3a**: Local climate disasters, to a larger extent than global ones, increase investor attention to climate change

> **H3b**: Local climate disasters, to a larger extent than global ones, abnormally increase green mutual fund flows through higher climate change awareness

3 Data

With this thesis, we thus test whether there is a clear effect from climate disasters on both investor attention and green mutual fund flows. Before setting out the methodology and steps we took to find such a possible effect, this chapter first outlines the data description, rationale and collection procedures we followed. Herein, it is important to note the scope of our thesis. All collected data refers to the period between May 2018 and December 2021, which are taken as natural cut-offs. Our primary designator for 'green' mutual funds is the Morningstar-published LCD label, further explained below, which saw its introduction in May 2018. Furthermore, given the inherent time lag between a climate disaster and its measured impact, we took December 2021 as the period end, to exclude those events which are too recent to have any measured impact. Geographically, our thesis focuses on both the United States, as well as the five largest economies in Europe (with the exclusion of Russia). Besides wanting to extend on prior fully US-focused research, this geographic scope is defined by its readily available data and its relatively unhindered freedom of press (RSF, 2021), the latter securing the link between a climate disaster and subsequent unincumbered news coverage. With the above, our scope further adds to current literature given its recency and its extended geographic coverage which includes the primary economies in Europe. Hereunder, the data collection steps are set out as follows, first is the coverage of climate disaster data and second is the Google search volume data, both of which are accompanied by a descriptive table and graph respectively. Last is the collected mutual fund data, which is subsequently presented in a descriptive statistics table.

3.1 Climate disaster data

The primary determinant in our source for climate disaster data was the geographic scope. US-focused papers have generally used the SHELDUS database (Marshall et al., 2021; Bernile et al., 2021; Alok et al., 2020), while literature with a more global angle has used EM-DAT data (El Ouadghiri et al., 2021; Kollias and Papadamou, 2016). The two databases are relatively similar in terms of output and data availability, however, it must be noted that the SHELDUS database is more detailed. This database covers county-level natural hazards and therefore includes significantly more events, seemingly tracking every reported disaster from the US National Center for Environmental Information. Given our geographic scope, as well as our focus on larger-damage events, we obtained our data on climate disasters from the EM-DAT database.

The Emergency Events Database, or EM-DAT, is a data tool developed by the Centre for Research on the Epidemiology of Disasters ('CRED') and launched in 1988 with support from the WHO and the Belgian government. This publicly accessible database, which has free access for non-commercial purposes, has tracked essential core data for mass disasters since 1900 and is updated daily. For recognition in the database, the CRED uses entry criteria such as: at least 10 deaths, at least 100 people affected or the allocation of a GLIDE number (Global Identifier; for larger-scale disasters), of which at least one of the criteria must be met. As such, the database only contains so-called mass disasters, whose information is directly obtained from credible sources such as the UN, (non-)governmental agencies, research institutes or press agencies.

For relevant data to our proposed study, we filtered the database for disasters classified as 'Natural', thereby excluding technological disasters such as industrial accidents (e.g. gas leaks and chemical spills). Then we excluded subgroups such as geophysical disasters (e.g. earthquakes and volcanic eruptions), which have a less clear link to climate change. Last, we filtered the dataset for the May 2018 to December 2021 time period. These search filters resulted in a database of 1,285 natural disasters. For further details on the filtering procedure, additional guidance is provided in Table A in the Appendix.

For use in our analyses, we subsequently ranked the disasters by scale in their respective geographies, with the largest events forming the selections as depicted in Table I. Magnitude-wise, we did so through a two-pronged approach that considers both relative magnitude compared to country-GDP levels (Bourdeau-Brien and Kryzanowski, 2020), as well as the El Ouadghiri et al. (2021) approach, in that we subsequently considered those events which impacted the most amount of people and/or caused the most financial damage, while also having newsworthy and attention-grabbing potential in light of climate change. In terms of geography, we considered two event sets. One set is limited to the six in-scope countries in our study, whereas the other concerns the largest disasters globally. This split allows us to study the effect of local event salience, in comparison to global larger-magnitude disasters. Therein, the latter likely form more distinct examples of climate change consequences and they also have the potential to generate universal news attention (Wu, 2000).

Table I: Descriptions and Consequences of Selected Climate Disasters

This table shows the selected climate disasters within the May 2018 - December 2021 period, inclusive. Panel A covers those events taken place in the USA, Germany, United Kingdom, France, Italy and Spain, and are filtered based on relative size impact compared to GDP or otherwise their attention-grabbing impact, in such a way that the list is limited to a minority share of the most impactful disasters in a given country. Panel B takes into account similar filters yet specified to include only the 2 largest disasters per continent. By design, events in Panel B which occured in the same countries as Panel A, overlap between the Panels. All data is obtained from the EM-DAT database, and where appropriate complemented with datapoints found in external credible sources such as news outlets and insurance damage reports. Total damages are reported in USDm. * denotes two disasters overlapping in terms of geography and date, as such being treated as the same observation in the dummy methodology of our core regressions, for that given month.

Panel A - Local

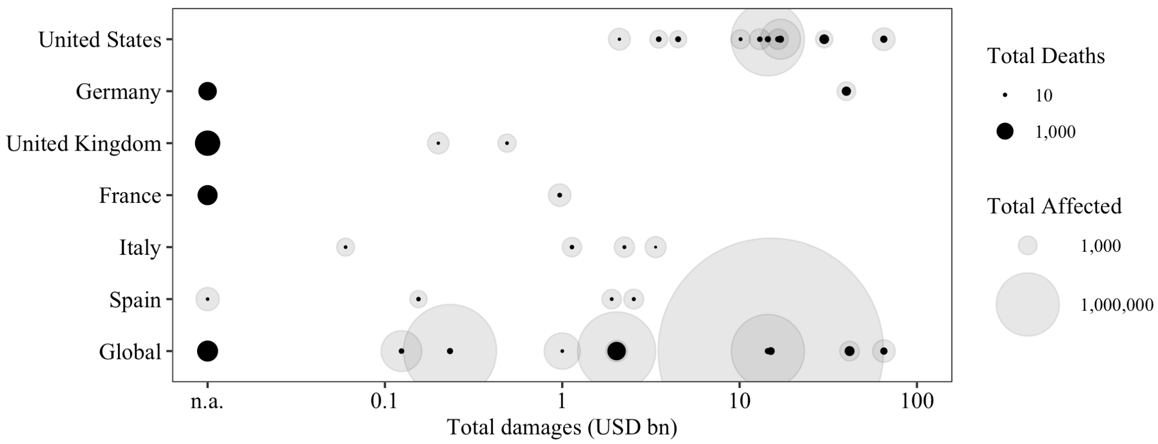
Geography	Start date	End date	Type	Event name	Casualties	Affected people	Total damages
USA	12/09/2018	18/09/2018	Storm	Hurricane Florence	53	1,500,000	14,430
USA	10/10/2018	11/10/2018	Storm	Hurricane Michael	49	5,000	16,491
USA	08/11/2018	25/11/2018	Wildfire	Camp Fire	88	250,000	17,006
USA	14/03/2019	31/03/2019	Flood	Missouri Flooding	5	2,000	10,123
USA	10/04/2020	14/04/2020	Storm	n.a.	38	200	3,500
USA	17/05/2020	20/05/2020	Flood	n.a.	1	10,000	2,100
USA *	01/06/2020	31/12/2020	Drought	Western US Drought	45	n.a.	4,500
USA *	27/08/2020	28/08/2020	Storm	Hurricane 'Laura'	33	6,500	13,000
USA	10/02/2021	20/02/2021	Storm	n.a.	235	10	30,000
USA	29/08/2021	01/09/2021	Storm	Tropical storm 'Ida'	96	14,000	65,000
Germany	23/07/2018	09/08/2018	Extr. Temp.	n.a.	1,230	n.a.	n.a.
Germany	12/07/2021	15/07/2021	Flood	n.a.	205	906	40,000
United Kingdom	25/07/2019	26/07/2019	Extr. Temp.	n.a.	900	n.a.	n.a.
United Kingdom	07/11/2019	08/11/2019	Flood	n.a.	1	8,440	200
United Kingdom	28/02/2020	28/02/2020	Flood	n.a.	3	480	488
United Kingdom	31/07/2020	31/07/2020	Extr. Temp.	n.a.	2,556	n.a.	n.a.
France	22/07/2018	05/08/2018	Extr. Temp.	n.a.	1,500	n.a.	n.a.
France	24/06/2019	28/06/2019	Extr. Temp.	n.a.	567	n.a.	n.a.
France	21/07/2019	27/07/2019	Extr. Temp.	n.a.	868	n.a.	n.a.
France	02/10/2020	03/10/2020	Storm	Storm 'Alex'	18	12,980	967
Italy	29/10/2018	04/11/2018	Storm	Storm 'Adrian'	12	2,200	1,134
Italy	27/11/2020	28/11/2020	Flood	n.a.	3	250	60
Italy	24/07/2021	26/07/2021	Wildfire	n.a.	n.a.	6,960	3,360
Italy	11/08/2021	12/08/2021	Wildfire	n.a.	5	4,640	2,240
Spain	09/10/2018	11/10/2018	Flood	n.a.	13	n.a.	155
Spain	11/09/2019	16/09/2019	Flood	n.a.	7	3,500	2,531
Spain	08/01/2021	12/01/2021	Storm	Filomena	4	2,500	1,900
Spain	28/11/2021	13/12/2021	Flood	n.a.	2	17,500	n.a.

Panel B - Global							
Geography	Start date	End date	Type	Event name	Casualties	Affected people	Total damages
Africa (Mozambique)	14/03/2019	15/03/2019	Storm	Cyclone 'Idai'	1,234	1,772,786	2,025
Africa (Tanzania)	24/04/2019	26/04/2019	Storm	Cyclone 'Kenneth'	53	2,745,405	233
Americas (USA)	12/09/2018	18/09/2018	Storm	Hurricane Florence	53	1,500,000	14,430
Americas (USA)	28/08/2021	02/09/2021	Storm	Tropical storm 'Ida'	96	14,000	65,100
Asia (Japan)	06/10/2018	07/10/2018	Storm	Typhoon 'Kong-Rey'	3	174,000	1,000
Asia (India)	17/05/2020	20/05/2020	Storm	Cyclone 'Amphan'	120	20,601,100	15,000
Europe (West)	19/07/2019	27/07/2019	Extr. Temp.	n.a.	1,669	n.a.	n.a.
Europe (West)	12/07/2021	18/07/2021	Flood	n.a.	250	3,096	41,700
Oceania (Australia)	27/01/2019	09/02/2019	Flood	n.a.	3	9,900	2,025
Oceania (Fiji)	04/04/2020	09/04/2020	Storm	Cyclone 'Harold'	34	265,126	124

The total selection comprises extreme temperatures, wildfires, storms, floods and droughts primarily. It can be observed that US-based events dominate Panel A, simply because of the higher number of high-impact natural disasters recorded there within the time frame. Compared to most disasters in the United States, European climate events seemingly have lower financial damages, albeit primarily caused by the nature of different disasters. As primarily observable from the United Kingdom, France and Germany, extreme temperatures in the form of heatwaves are a far more dominant natural disaster type in Europe than in the US. In line with the EM-DAT database, the total affected people and financial damages for these events remain excluded from our dataset, as the number of temperature-affected people, in light of it being perceived as a disaster, can hardly be defined. Additionally, financial damages caused by temperature itself are mostly indirect. For a visual representation of the disasters and their consequences as included in our analyses, please see Figure II below.

Figure II: Impact-by-Geography Analysis of Climate Disasters

This figure provides illustrative background information on the magnitude and subsequent attention-grabbing potential of the climate disasters included in our study. All data included is obtained from the included events as per Table I. The log-scaled X-axis refers to financial damages of the climate disasters in USD bn, with n.a. events having no reported damages. The events are furthermore sorted by the six in-scope geographies, as well as a row for the global events. Bubble sizes refer to the total number of casualties, in the darker shade, and the total number of affected people, in the lighter shade, for each of the disasters.



3.2 Google search volume data

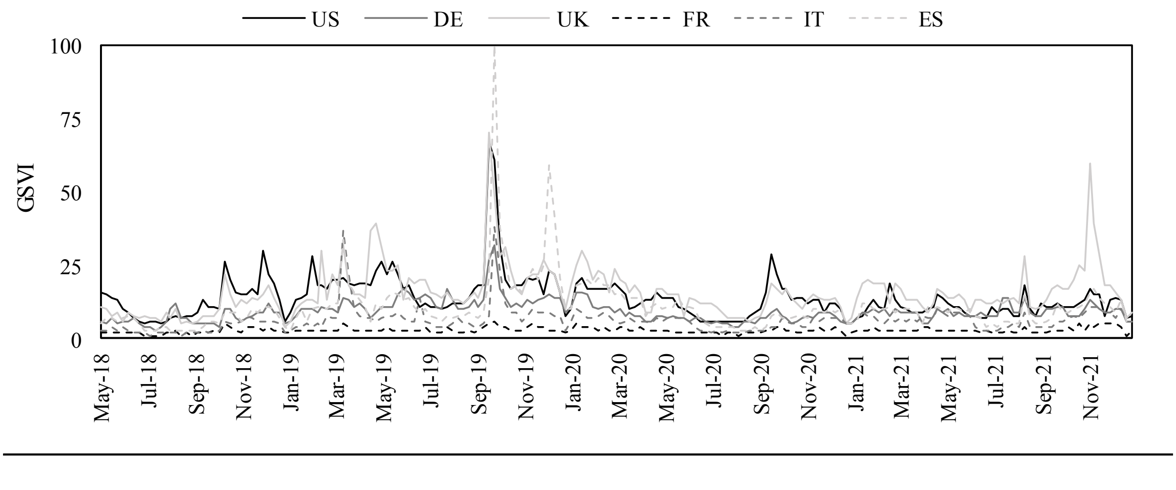
Our initial analyses aim to show to what extent climate disasters locally as well as globally impact investor attention. Therein, we follow e.g. Choi et al. (2020) and Ma et al. (2022) by using GSVI data to proxy investor attention. As stated earlier, since Google remains the dominant search engine worldwide, and since mutual fund investors are to a large extent non-professional investors, GSVI data is deemed a highly relevant proxy for investor attention in our study.

Since 2006, Google has made its relative search volume data publicly available through Google Trends. According to Google, its search volume data refers to a sample only, yet is still representative given the high amount of traffic that its search engine processes every day. Subsequently, Google normalizes the search data by taking the fraction of a certain search term or topic compared to the geography and time range chosen, which is then scaled on a range between 0 and 100 based on a search's proportion relative to other searches. As such, it must be noted that the retrieved data from Google is susceptible to the exact search based on the search terms, time frame or the compared geographies. Linked to this, another aspect and limitation to take into account with this methodology is that there is a certain search volume threshold. Below this threshold, GSVI is either unavailable, if too few searches in general, or set to 0, if too few or unavailable searches compared to e.g. another search term or geography. Furthermore, Google differs between search terms and topics, with the former referring to a specific search term only, and the latter taking into account a search term as well as related terms, such as synonyms and translations in different languages.

We collected GSVI data on the topics of 'Climate change' and 'Global warming'. With that, we follow prior research by e.g. El Ouadghiri et al. (2021). Rather than taking certain event types or climate disasters as search terms, 'Climate change' and 'Global warming' as topics provide a direct link to climate awareness. Additionally, as mentioned above, by taking the topic instead of the search term, we account for related terms, synonyms and different language-denoted search terms. We collected weekly GSVI data for each of our six in-scope geographies separately, for the May 2018 to December 2021 time period. As such, having six country-specific data frames for the search volumes per topic, each of which peaks at 100. In line with Choi et al. (2020), we then took the natural log change in search volume for the variables' consideration in our regression analyses.

Figure III: Country-by-Country Google Search Volume for 'Climate change'

This figure shows the pooled weekly Google search volume data for the United States, Germany, the United Kingdom, France, Spain, and Italy on the topic of 'Climate change', for the the May 2018 - December 2021 period, inclusive. The data has been retrieved from Google Trends and shows the relative search volume from 0-100, in comparison to the highest search volume across the period and the pooled dataframe of all six countries combined.



The limitation that search volume below a certain lower threshold is unavailable, almost certainly counteracts our study as a relative increase in search volume is likely more prominent for countries that have generally low search interest in the topic compared to countries with consistently higher search volume. To combat this, our study focuses on the topic of ‘Climate change’, given its noticeably higher search volume than ‘Global warming’. This results in a dataset without zero-value data points. Figure III above shows the relative search volume for the ‘Climate change’ search topic, which for illustrative purposes only is pooled for all the six countries at interest. Figure A shows a plot of pooled ‘Global warming’ search volume in the Appendix for reference.

3.3 Mutual fund data

We obtained survivorship-bias-free mutual fund data from Morningstar Direct. In May 2018, Morningstar announced and introduced the Carbon Risk Score, which ranks a fund's exposure to carbon risk. Simultaneously, the LCD label was launched, given to those funds which have low carbon risk scores and low fossil fuel exposure levels. As found by Ceccarelli et al. (2021), funds holding the LCD label received significantly larger flows, and on top of that, funds actively shifted portfolio holdings to reduce their Carbon Risk Scores. The importance of this label, together with its higher direct relevance to climate change, makes it a highly suitable variable in our analyses on potentially higher flows into 'green' funds compared to control funds.

At the time of writing, Morningstar Direct covers over 315k open-ended fund share classes in its database, for which it provides a wide variety of current and historical datapoints. To get an initial homogeneous raw dataset fitting to the scope of our analyses, we selected all those share classes which did not cover fixed-income or sector-specific products only. Furthermore, we defined our geographic scope by filtering on the Region of Sale for the six prior-defined in-scope countries, as this customer-facing data point is more appropriate for our attention-focused study than e.g. a fund's domicile. Combining these Investment Category and Region of Sale filters, we obtained an initial set of 41,213 share classes, as is further specified in the filtering procedure in Table A in the Appendix. For this set we obtained suitable share class-level variables, either corresponding to one data point per variable for e.g. general share class details, or corresponding to up to 44 month-level data points for the equal number of months in the May 2018 to December 2021 period.

First in computing the data, we aggregated the share classes to fund-by-region of sale level observations, leaving 17,559 aggregated share classes. Morningstar data showed the data points on a per-share-class basis, with a high number of funds issuing multiple share classes to target different subsets of investors. Given that a number of different share classes target different geographies, we aggregated the share classes on both the fund and region of sale levels, instead of on the fund level only. Hereby, we differentiate from e.g. the aggregation approach of Ceccarelli et al. (2021), yet given the scope of our study, which in particular looks at investor behavior within a certain geography, we argue this to better suit our analyses. The remainder of our aggregation approach does follow their study, in that we take the weighted average of share classes to generate aggregated returns and volatility, and we take other aggregated share class information from the largest underlying share class. This approach fits our study since the underlying portfolio of different share classes within the same fund does not actually vary on a share class basis. Similar to Ceccarelli et al. (2021) and Marshall et al. (2021) amongst others, we follow the approach by Sirri and Tufano (1998) to calculate fund flows. Their measure, as adopted in our analyses, computes fund flows as the monthly growth of total net assets, net of returns.

Table II: Descriptive Statistics

This table shows the descriptive statistics of climate disaster, search volume and mutual funds data within the May 2018 - December 2021 period, inclusive. DIS and GDIS cover the dummy variables for local and global climate disasters respectively, covering those events set out in Table I. GSVI covers Google search volume data on the topic 'Climate change', and GSVI adj. refers to the residuals of that dataset accounted for certain systematic movements and seasonality. The remaining statistics, as far as data was available, cover mutual funds data and are included on a monthly basis, for fund-by-region of sale level aggregated share class observations. Disaster data is obtained from the EM-DAT database, search volume data is obtained from Google Trends and mutual funds data is obtained from Morningstar Direct. Detailed further guidance on all variables is provided in Table B, in the Appendix.

	N	min	p25	mean	p50	p75	max	sd
FLOW	468,519	-12.55	-0.83	-0.05	0.00	0.21	22.72	2.70
NFLOW	468,519	0.00	38.62	47.89	47.53	54.02	100.00	20.45
DIS	468,519	0.00	0.00	0.18	0.00	0.00	1.00	0.38
GDIS	468,519	0.00	0.00	0.21	0.00	0.00	1.00	0.41
GREEN	468,519	0.00	0.00	0.16	0.00	0.00	1.00	0.36
Log TNA	468,519	12.66	16.32	18.08	17.88	19.56	27.95	2.16
Age	468,519	0.05	6.44	14.35	13.42	19.81	97.38	9.81
Log Age	468,519	2.89	7.76	8.30	8.50	8.89	10.48	0.80
Volatility	468,519	0.14	2.72	4.21	3.77	5.21	57.86	2.00
Return t-1	468,519	-98.87	-1.75	0.55	0.63	3.04	140.37	4.62
Globes	276,976	1.00	2.00	3.14	3.00	4.00	5.00	1.06
Stars	310,577	1.00	2.00	2.88	3.00	4.00	5.00	1.07
Δ1 Globe	468,519	-1.00	0.00	0.00	0.00	0.00	1.00	0.09
Δ5 Globe	468,519	-1.00	0.00	0.00	0.00	0.00	1.00	0.11
ΔStars	468,519	-1.00	0.00	0.00	0.00	0.00	1.00	0.31
GSVI	468,519	-0.05	0.79	1.01	1.00	1.18	2.47	0.35
GSVI adj.	468,519	-0.75	-0.11	0.00	0.00	0.11	0.55	0.20

Table II shows the descriptive statistics of the fund-by-region of sale level aggregated share class observations for the variables of interest in our research, for which detailed guidance is provided in Table B in the Appendix. Within our range of variables, most come directly from

Morningstar and, apart from aggregation as described above, are not further manipulated with the exception of FLOW and NFLOW which are trimmed at the 1st and 99th percentiles as well as TNA which is trimmed at the 1st percentile. In terms of our dependent variable of interest, NFLOW is additionally calculated, denoting the normalized fund flows as also included by Hartzmark and Sussman (2019). This variable further normalizes fund flows based on percentiles within total-net-asset-based deciles, thereby accounting for systematic noise of results that are driven by outliers or by volatile flows of smaller-sized funds. We compute the AGE variable as the time since inception of the oldest share class in the dataset. Furthermore, the variables ΔStars, Δ1 Globe and Δ5 Globes measure the change in assigned stars as well as the dummies for change into/ out of the 1 and 5 Globe ratings respectively. Besides, note that we follow Amihud and Goyenko (2013) in that we take the natural logarithms of TNA and AGE in our analyses. For monetary reference, the mean Log TNA of 18.08 in Table II corresponds to an average share class size of $1.1bn, on a fund-by-region of sale level aggregated basis. Last, we also include the GSVI variable, or its adjusted idiosyncratic variant, in some of the analyses on mutual fund flows. Note that here we used monthly GSVI data to match the fund flow data in our regressions. For further descriptive statistics on our core variables segmented by their geographical region of sale, this is included in Table C in the Appendix. Additionally, Table D displays the pairwise correlations for the variables described in Table II, substantiating the grounds on which we included the explanatory variables in our analyses.

4 Empirical results

This section provides the results of all analyses conducted to test the hypotheses as set out in Section 2.2. To that end, the analyses are presented in a similar order, comprising both their regression methodology and the subsequent results. First, we provide the results of our so-called local-on-local investor attention analyses, using OLS regressions on GSVI data to measure investor attention at times of same-country climate disasters. Following this, we use pooled linear regression models to establish differences in fund flows between green and non-green funds at times of same-country climate disasters. Subsequently, we analyze the results for both investor attention as well as mutual fund flow differences in our 'global vs. local' analyses, thereby studying the effect of global events. We link investor attention and fund flow results, as well as analyze the effect of global climate disasters in comparison to the effects of local climate disasters. Last, we present and analyze the results of robustness tests on our core analyses.

4.1 Local-on-local attention-grabbing effect

Initially, we establish the effect of climate disasters on investor attention. As described, we consider a selection of local climate disasters as portrayed in Table I, which are included in the following regression through the independent dummy variable DIS_t. We proxy investor attention by collecting and analyzing GSVI data, forming the dependent variable in this first analysis, which considers the search topic 'Climate change':

$$CC\ GSVI_t = a + b_1 DIS_t + b_2 OE_t + \gamma_2 T_2 + \cdots + \gamma_n T_n + e_t \tag{1}$$

Next to DIS_t, we control for other attention-grabbing events through OE_t in this analysis. As can be seen from Figure III, Google search volume into 'Climate change' sees a number of coinciding spikes across the countries, of which a considerable amount fall outside the scope of what can be explained by natural disasters. Specifically, it seems that the most attention-grabbing events denote climate strikes and global climate policy summits. In line with that, Ramelli et al. (2021) found that the March 2019 Global Climate Strike had a significant effect on investor attention as well as carbon-intensive stock prices. Based on that, we argue that GSVI data for a specific country comprises systematic search volume movements across countries, for which we control to have a more idiosyncratic measure from which we can infer country-specific attention spikes. In Regression (1), this is done by controlling for OE_t, denoting non-disaster climate attention events as specified in Table E in the Appendix. Alongside this, we included year and month fixed effects (T), following the methodologies of e.g. Choi et al. (2020) and Ghosh and Zhang (2021), accordingly accounting for seasonality in the attention patterns.

Our first hypothesis, H1, refers to the expectation that local natural disasters have a positive effect on investor attention within the same country as where these natural disasters take place. Regression (1) tests this, with the results displayed in Table III. The findings show that, controlling for seasonality and other attention-grabbing events related to climate change, disaster-affected months denoted by DIS_t have positive loadings across the board, with all coefficients statistically significant at sub-10% levels. Accordingly, we can state with relatively high statistical certainty that natural disasters in these countries are positively related to investor attention, all else being equal.

Table III: The Effect of Climate Disasters on Same-Country 'Climate change' Attention

This table shows results of OLS regressions of weekly Google search volume index ('GSVI') data, for the topic 'Climate change', on dummy variable DIS. The latter indicates the occurance of a climate disaster, as per the selection in Table I, for that given week within the model-corresponding country. The models in this table control for dummy variable OE, indicating whether one of the events as specified in Table E occurred in that given week. All models include GSVI data for the May 2018 - December 2021 period, inclusive. All regressions control for month and year fixed effects. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	GSVI 'Climate change' (weekly)					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS	0.117**	0.515***	0.321*	0.261**	0.221*	0.218*
	(0.055)	(0.116)	(0.163)	(0.104)	(0.128)	(0.120)
OE	0.346***	0.334***	0.389***	0.255***	0.541***	0.581***
	(0.080)	(0.066)	(0.097)	(0.075)	(0.093)	(0.099)
Observations	192	192	192	192	192	192
Adjusted R^2	0.15	0.17	0.10	0.09	0.17	0.21
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Given the log nature of the dependent variable, we cannot intuitively infer the economic significance of the point estimates in Table III. Nonetheless, we can observe from the results that the positive relation between local disasters and investor attention is highest for Germany and lowest for the United States. The latter is potentially linked to the larger number of disasters included in the US-based analysis. On the back of higher susceptibility to natural disasters in our time frame, this could in turn provide a reason for its lower point estimate, as for a country more prone to extreme weather events, every next natural disaster triggers relatively less additional attention. Another likely reason relates to the larger geographic size of the US, for it being reasonable that e.g. the Missouri floodings generate less attention in a more distant state like California. Furthermore, we find that the results for France, in Table III, are around the midpoint considering the magnitudes of the countries' shocks to investor attention at times of climate disasters. It is interesting to note however that France is one of the few countries globally which reported higher aggregate search volume for the topic 'Global warming'. Regression results for search into the latter are reported in Table F in the Appendix, and show how France's results do show significant loadings when analyzing 'Global warming' as a topic. Taking into account all our attention findings, we observe that especially in Germany, local natural disasters coincided with hefty spikes in search volume. In our analyses, this implies that the set of Germany-located disasters, comprising the 2018 heatwave and the 2021 flooding, saw the most significant same-country climate change attention shocks.

Drawing conclusions from these results, we find the relation between same-country climate disasters and investor attention to be clearly positive across the board. These findings imply that a considerable amount of investor attention is generated spontaneously. This is further substantiated through the findings for OE_t, evidencing that events such as climate strikes and summits coincide with observably higher levels of attention, more so having a larger effect than natural disasters. While accounting for these events and seasonality, certain idiosyncratic positive shocks to search volume persist, additionally showing some country-to-country differences in our analyses. We find that the US stands out through its observably lower coefficient compared to the European countries, showing a lower attention-grabbing ability in our sample period, while the opposite is notable for Germany. Overall, the results confirm our set-out hypothesis H1: *Local climate disasters increase same-country investor attention to climate change*, while the findings additionally serve as building blocks for a judgment on H3a, which we further refer to back in the results part of our 'global vs. local' analyses.

4.2 Local-on-local mutual fund flow effect

On the back of the shown positive relationship between local climate disasters and same-country investor attention, this section analyzes the extent to which these results in turn lead to changed investment behavior. Namely, are these attention-grabbing disasters followed up by differences in fund flows between green and non-green mutual funds. In examining the direct effect of climate disasters on green mutual fund flows, we initially consider a pooled linear model using the following regression:

$$FLOW_{i,t} = a + b_1 DIS_t + b_2 GREEN_{i,t} + b_3 \left(DIS_t * GREEN_{i,t}\right)$$
$$+ gControls + \gamma_2 T_2 + \cdots + \gamma_n T_n + \delta_2 S_2 + \cdots + \delta_n T_n + e_{i,t} \quad (2)$$

Simultaneously, we consider the mentioned remarks of Hartzmark and Sussman (2019), on including a normalized flow variable to ensure that results are not driven by systematic noise. As such we consider Regression (2) alongside a near-duplicate version which considers normalized flows ($NFLOW_{i,t}$) as dependent variable. With these regressions, the interaction variable of $DIS_t * GREEN_{i,t}$ is the independent variable of interest in both cases. This independent variable builds upon DIS_t and $GREEN_{i,t}$, as outlined in Table B in the Appendix. The LCD label gets awarded on a quarterly basis, which for measurement in our regression is used as a dummy variable that looks at whether the fund was awarded the label in the most recent quarterly measurement point. As such, $GREEN_{i,t}$ in our regressions is set to 1 if the fund received the label in the latest round, or 0 otherwise. DIS_t is the dummy variable indicating whether one of the selected climate disasters (Table I) took place in a given month, in the same geographic region as a fund's region of sale. The dummy variable is set to 1 if that is the case, or 0 otherwise. Similar to Ceccarelli et al. (2021), we include fund characteristics linked to fund flows, such as Log AGE, Log Assets, (1-month lagged) Returns and Volatility, as control variables in the regression. Similar to the descriptive LCD label, descriptive rankings as the Globe and Stars ranking are proven to have predictive power when it comes to mutual fund flows (Hartzmark and Sussman, 2019), and are therefore also included as control variables. In Regression (2), all these control variables are denoted by $gControls$. Last, we follow Amman et al. (2019), Chen et al. (2021) and others in the use of month (T) and style (S) fixed effects, with the latter referring to Morningstar Categories. Standard errors are double clustered on month and style to obtain fully robust standard errors and test statistics.

Table IV: The Effect of Climate Disasters on Same-Country Mutual Fund Flows

This table shows results of pooled linear regression models of monthly mutual fund flows, on dummy variable DIS and the interaction of this variable with dummy GREEN. DIS indicates the occurance of a climate disaster, as per the selection in Table I, for that given month within the model-corresponding country. GREEN indicates whether a fund has been allocated the Morningstar Low Carbon Designation in the latest quarterly review. All models include fund flow data for the May 2018 - December 2021 period, inclusive. All regressions control for month and style fixed effects, as well as clustered standard errors. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Flows					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS x GREEN	0.104*	0.208**	0.383**	0.199*	0.121	0.100**
	(0.054)	(0.093)	(0.173)	(0.091)	(0.173)	(0.039)
DIS	0.006	0.250*	-0.056	0.034	-0.117	0.035
	(0.077)	(0.121)	(0.124)	(0.070)	(0.081)	(0.050)
GREEN	0.133*	0.318***	0.258**	0.173**	0.546**	0.125
	(0.069)	(0.079)	(0.112)	(0.068)	(0.232)	(0.110)
Log TNA	0.037***	0.132***	0.075***	-0.014	0.241***	0.065**
	(0.011)	(0.027)	(0.021)	(0.025)	(0.065)	(0.023)
Log Age	-0.857***	-0.559***	-0.794***	-0.407***	-0.593***	-0.296*
	(0.049)	(0.058)	(0.096)	(0.058)	(0.175)	(0.138)
Return t-1	0.024**	0.020	0.000	-0.001	0.005	0.006
	(0.010)	(0.011)	(0.010)	(0.011)	(0.025)	(0.008)
Volatility	-0.065***	0.005	-0.043	0.002	-0.007	-0.010
	(0.019)	(0.031)	(0.032)	(0.024)	(0.066)	(0.016)
Δ1 Globe	-0.038	-0.047	-0.122	0.136	0.065	0.009
	(0.044)	(0.101)	(0.100)	(0.139)	(0.255)	(0.094)
Δ5 Globes	0.093	0.059	-0.167	-0.008	0.004	-0.059***
	(0.061)	(0.115)	(0.185)	(0.089)	(0.095)	(0.018)
ΔStars	-0.024	0.039	-0.052*	-0.007	0.102	-0.063
	(0.025)	(0.048)	(0.027)	(0.038)	(0.114)	(0.075)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.09	0.04	0.09	0.04	0.15	0.03
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

The results of Regression (2) are depicted in Table IV for net fund flows. Point estimates of $DIS_t * GREEN_{i,t}$ in the regressions show us that for all columns but Italy, having an insignificant coefficient, the results imply more flows into green funds, relative to control funds, at times of local natural disasters. Other than Italy, all coefficients are positive and statistically significant at sub-10% levels. The stand-alone variable for the occurrence of a local natural disaster in a given country, DIS_t, provides coefficient values that lack overall statistical significance, indicating that we cannot deduct any clear relation between climate disasters and control funds' flows. This makes the findings from our interaction variable, $DIS_t * GREEN_{i,t}$, even more notable. The coefficient results for e.g. the US imply that control funds see an increase in flows by +0.6 basis points, while green funds rise +11 basis points (coefficients of 0.006 + 0.104), as such indicating a 10 basis points difference, all else being equal. Across the countries, this difference ranges from 10 (US, ES) to 38 basis points (UK). Compared to monetary terms, this translates into a total of $22.7bn, $0.8bn and $0.6bn higher flows to green funds in the United States, Spain and the United Kingdom respectively, per disaster-affected month. Please note that the US' disproportionately higher dollar figure for fund flows relates to the substantially larger size of their mutual fund market. To a large extent, the basis point difference shows an extension of the GSVI-proxied attention-grabbing effect, where US-based loadings were similarly lower, while results for especially Germany, the UK and France show both higher investor attention levels as well as larger relative inflows into green funds, compared to control funds, at times of natural disasters. As for the other explanatory variables, the LCD label ($GREEN_{i,t}$) and a fund's size, depicted through the natural log of *TNA,* have the most clearly positive effects on net fund flows overall. At the same time, the number of years since the inception of a fund's oldest share class is most clearly negatively related to fund flows for all six countries. Other control variables mostly lack statistical significance, yet overall the findings are in line with prior papers by e.g. Ceccarelli et al. (2021).

Overall, our results show positive associations between the interaction term $DIS_t * GREEN_{i,t}$ and the dependent variable $FLOW_{i,t}$. Table V, below, extends upon Regression (2) by including analyses on the lagged effect of natural disasters (Panel A), the indirect effect through Google search volume (Panel B) and the before-mentioned analysis using $NFLOW_{i,t}$ as dependent variable (Panel C). These analyses generally strengthen our findings of increased flows into green funds, through positive coefficients on $DIS_t * GREEN_{i,t}$, while also indicating that there is no indirect effect through GSVI data.

Table V: Analyses on the Link between Climate Disasters and Same-Country Fund Flows

This table considers further regression models of quarterly (Panel A), monthly (Panel B) and normalized monthly flows (Panel C), on the interaction of variables DIS and GREEN. DIS indicates the occurance of a climate disaster, as per Table I, for that given month within the model-corresponding country. Note that for Panel A only, DIS indicates the first month of a new climate disaster, rather than any disaster-affected month. GREEN denotes a fund that has been allocated the Morningstar Low Carbon Designation in the latest quarterly review. Panel B further includes an interaction term with variable GSVI adj, denoting same-country Google search volume into the topic 'Climate change', accounting for certain systematic movements and seasonality. All models include fund flow data for the May 2018 - December 2021 period, inclusive, thereby allowing for less observations in a quarterly analysis, as compared to a monthly analysis, due to data availability. All regressions control for month and style fixed effects, as well as clustered standard errors. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) US	(2) DE	(3) UK	(4) FR	(5) IT	(6) ES
Panel A: Quarterly flows						
DIS x GREEN	0.209	0.526*	0.843**	0.428***	-0.328	0.338
	(0.168)	(0.253)	(0.297)	(0.116)	(0.310)	(0.300)
Observations	127,990	44,460	46,832	73,194	29,727	123,006
Adjusted R^2	0.14	0.07	0.14	0.06	0.20	0.06
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Monthly flows						
DIS x GREEN	0.111*	0.310**	0.390**	0.211*	0.077	0.118**
	(0.057)	(0.136)	(0.163)	(0.111)	(0.196)	(0.043)
GSVI adj. x GREEN	-0.113	-0.323	0.052	-0.190	0.381	0.271*
	(0.126)	(0.198)	(0.160)	(0.298)	(0.401)	(0.134)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.09	0.04	0.09	0.04	0.15	0.03
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Normalized monthly flows						
DIS x GREEN	1.373**	2.347**	3.275***	2.434***	3.160**	0.722***
	(0.444)	(0.917)	(1.011)	(0.724)	(1.160)	(0.193)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.12	0.07	0.11	0.05	0.19	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

Enhancing the positive relation between natural disasters and green fund flows, Panel C in Table V shows high significance for $DIS_t * GREEN_{i,t}$ when regressing on normalized flows. The point estimates here with statistical significances at the sub-5% level, indicate that the positive relation between local natural disasters and green fund flows persists when controlling for systematic noise from outliers or smaller funds' volatile flows. Despite giving little indication on the economic significance of the coefficients, this further sustains our finding that local natural disasters generally coincide with increased fund flows into green funds relative to control funds.

Panel A of Table V indicates that the positive shocks to green mutual funds during a disaster-affected month are still observable for Germany, France and the United Kingdom when compared to fund flows in the following quarter (current month plus the following two months), instead of merely the current month. Similarly to Table IV, we find that the results of $DIS_t * GREEN_{i,t}$ provide positively-signed coefficients, yet with generally larger loadings in the quarterly analysis. In line with the visual of Figure I, presented in the introduction, these results imply that the higher flows towards green funds relative to non-green funds are observed not just when awareness of the disaster starts, but with a lag of up to three months. Results in Table G in the Appendix further enhance this, as they show slightly lower coefficients for the interaction term when analyzing the following four months (triannual flows), implying that the difference between flows to green and control funds disappears after three months. One reason inherent in our methodology is that some events, even though lasting some days only, occur in two months. Other events actually do span timeframes longer than 30 days (in our study, primarily the drought in the United States). As these reasons concern only a handful of events in our study, this lagged effect also suggests a behavioral influence, for it being reasonable that investment decisions are not a top priority, or even directly possible, for retail investors who are experiencing climate disasters.

To measure the extent to which GSVI-proxied investor attention forms a mediator between climate disasters and changing fund flows, Panel B includes the idiosyncratic residuals of country-specific search volume, accounting for systematic movements and seasonality, as a control variable. For further guidance on this adjusted GSVI variable, see Table B in the Appendix. Contrarily to our initial beliefs, we do not find a significant link between $GSVI\ adj._t * GREEN_{i,t}$ and $FLOW_{i,t}$. This shows that there is only a direct relationship between climate disasters and green fund flows, but no mediating effect through Google search volume.

Despite prior studies' findings, GSVI data may thus not be a reliable measure for investor attention in this setting. One explanation could be that those people who search for 'Climate change' on Google, are simply not the same people who invest in mutual funds. As per Anderson and Robinson (2021), beyond holding green preferences, people need to have the financial literacy as well as the means required to act on this information, which is not a given.

As the above results fail to show that Google search volume is associated with fund flow movements, this questions the presence of an attention-triggered behavioral effect. Still, we argue that our results indicate such a shift at times of climate disasters. As Sisco et al. (2017) stated, the significant behavioral shift generated right after a weather event's occurrence, compared to right before the event, signals the importance of actually experiencing the event. Admittedly, this is intuitively much less clear, if at all, when measured on a monthly level as we do. Yet, a notable difference between post-natural-disaster fund flows into green funds versus control funds would in itself likely have a behavioral driver. As found by Choi et al. (2020), following abnormally high temperatures, boosted demand for low carbon funds relative to higher carbon funds is a likely sign for increased recognition of the effects of climate change on people's investments. This is in line with intuition, as other mostly financial reasons would fail to explain why climate disasters are structurally followed by a different level of flows towards green funds versus non-green funds.

To sum up, our findings generally imply that green mutual funds see increased fund flows relative to control funds, at times of same-country natural disasters. We find that this positive difference is apparent from fund flows in five out of our six in-scope geographies, with additional analyses with normalized flows indicating that this difference is statistically significant across the board. The results furthermore point to a lagged difference in some of our sampled countries. As per our analyses, this difference persists for one quarter before diminishing, implying that increased fund flows towards green funds can hold for up to three months after people first become aware of a natural disaster. The mediating role of GSVI-proxied investor attention is however weak in this setting, showing no significant relation. This in part questions the behavioral link to increased green fund flows, yet in line with prior literature, we argue that this is still likely implied by the clear difference in flows to green versus control funds at times of natural disasters. As such, we find partial support for our hypothesis H2: *Local climate disasters abnormally increase same-country targeted green mutual fund flows through increased climate change awareness.*

4.3 Global vs. local: the salient influence of disaster proximity

On the back of the prior analyses which we used to test both H1 and H2, we follow a similarly developed model focused on global events, to test H3a and H3b. Here we test both the effect on investor attention, as well as the effect on green mutual fund flows, as caused by a selection of the largest global climate disasters. As such, we use a model, in parallel to the local model, comprising Regressions (1) and (2), wherein we additionally analyze for $GDIS_t$, to test for the global natural disasters as outlined in Panel B of Table I. This allows for a comparability analysis in this section, focused on the local-vs-global salience of these events. Below we report on their results.

Table VI: The Effect of Global Climate Disasters on 'Climate change' Attention

This table shows results of OLS regressions of weekly Google search volume index ('GSVI') data, for the topic 'Climate change', on dummy variables DIS and GDIS. DIS indicates the occurance of a climate disaster, as per the selection in Table I Panel A, for that given week within the model-corresponding country. GDIS indicates the occurance of a disasters as per Table I Panel B, for that given week beyond the model-corresponding continent. All models include GSVI data for the May 2018 - December 2021 period, inclusive. All regressions control for month and year fixed effects, as well as systematic search volume changes through the control for *Other events,* as outlined in Table E. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	GSVI 'Climate change' (weekly)					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS	0.106*	0.522***	0.319*	0.250**	0.213	0.221*
	(0.058)	(0.116)	(0.165)	(0.105)	(0.129)	(0.121)
GDIS	0.067	0.075	0.009	0.098	0.060	-0.022
	(0.105)	(0.084)	(0.124)	(0.095)	(0.118)	(0.126)
Observations	192	192	192	192	192	192
Adjusted R^2	0.15	0.17	0.09	0.09	0.17	0.21
Other Events	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table VI shows the results of the investor attention analyses as set up through Regression (1), here including both $GDIS_t$ and DIS_t. Compared to Table III, the results follow from considering the same search volume as the dependent variable, accounting for the same

Other events and seasonality as controls, yet with the global disasters included as the independent dummy variable. As can be further seen from Figure II, these global disasters consider structurally high-impact events worldwide. Despite generally positively-signed coefficients in Table VI, global disasters cannot be associated with certain search volume movements, lacking statistical significance below the 10% level. Including $GDIS_t$ in the attention analyses, compared to Table III, furthermore shows only marginal changes in the results for DIS_t, amplifying that local natural disasters include an attention trigger beyond that of the largest climate disasters globally.

The findings imply that global climate disasters have no clear attention-grabbing capacity in our six countries of interest. Contrarily to the findings by local natural disasters, the results show no statistical significance from global events. This indicates that, despite the severity of worldwide climate disasters, being a multitude of that of the natural disasters within Europe or the US, people need events in their close proximity in order to gain their attention. These findings are in line with that of prior literature (by e.g. Alok et al. (2020); Han et al. (2020)), in that they show that local disasters are more salient, accordingly generating more investor attention. As such, we find support for H3a: *Local climate disasters, to a larger extent than global ones, increase investor attention to climate change*.

Second in our 'global vs. local' comparison, we consider the results of Regression (2) including $GDIS_t$, which are depicted below in Table VII. Similar to the investor attention results, our findings here lack statistical significance. Both the results for the interaction term with green funds, as well as for $GDIS_t$ as a standalone variable, are in general insignificantly different from zero. As such, this indicates that fund flows, regardless of being to green or control funds, are not associated with the occurrences of global climate disasters. Compared to the results in Table IV, the findings for control variables match across all countries, as such being left out from detailed depiction in Table VII.

In the prior section, we found that the GSVI data had no clear mediating effect. Nonetheless, it is interesting to note that for both the local-on-local analysis, as well as for the findings from global disasters, there are observable similarities in signs and significances from the attention regressions to the fund flow regressions. Similar to H3a, we find supportive results for H3b: *Local climate disasters, to a larger extent than global ones, abnormally increase green mutual fund flows through higher climate change awareness*. We find that these hypothesis-confirming results are in line with the differences in magnitude between the results of prior global-event focused studies by e.g. El Ouadghiri et al. (2021) and Kollias and Papadamou (2016), and local-event focused results of Marshall et al. (2021). Explanations to this finding link into the prominence of close-proximity events and their stronger-perceived impact, as discussed also in Bernile et al. (2021).

Table VII: The Effect of Global Climate Disasters on Mutual Fund Flows

This table shows results of pooled linear regression models of monthly mutual fund flows, on dummy variables GDIS and DIS, and their respective interactions with dummy GREEN. DIS indicates the occurance of a climate disaster, as per the selection in Table I Panel A, for that given month within the model-corresponding country. GDIS indicates the occurance of a global climate disaster, as per the selection in Table I Panel B, for that given month beyond the model-corresponding continent. GREEN indicates whether a fund has been allocated the Morningstar Low Carbon Designation in the latest quarterly review. All models include data for the May 2018 - December 2021 period, inclusive. All regressions control for month and style fixed effects, as well as clustered standard errors, and the same control variables as in Table IV. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Flows					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS x GREEN	0.102	0.348*	0.382**	0.201**	0.005	0.095*
	(0.069)	(0.162)	(0.173)	(0.086)	(0.206)	(0.044)
DIS	0.027	0.248*	-0.055	0.022	-0.323*	0.052
	(0.120)	(0.120)	(0.122)	(0.072)	(0.163)	(0.055)
GDIS x GREEN	0.004	-0.227	0.036	0.079	0.316	0.006
	(0.093)	(0.136)	(0.105)	(0.115)	(0.360)	(0.094)
GDIS	-0.045	-0.016	-0.003	-0.159**	0.482	-0.138
	(0.161)	(0.046)	(0.063)	(0.067)	(0.301)	(0.078)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.09	0.04	0.09	0.04	0.15	0.03
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

4.4 Robustness tests

To strengthen the results obtained with the regression analyses, we conduct robustness tests to expose our results to, and see if they still hold under, a number of sensitivity analyses on the key variables at interest. Below we present the methodologies and their results for our robustness tests, which respectively use the inclusion of a disaster index instead of a dummy variable and the inclusion of fund fixed effects. The regressions below, even though set out for dependent variable $FLOW_{i,t}$, are simultaneously considered for $NFLOW_{i,t}$.

Disaster index

First, we consider to what extent the measurement methodology of the disasters as specified in Table I impacts our results. Specifically, we recognize that our initial dummy measure fails to account for the magnitude of different disasters, classifying them all as identical in the eyes of our regression. Moreover, as specified in Table I, there are certain events that overlap in terms of the months in which they occur. Thus far, these overlapping events have been considered as the same observation within the monthly dummy variable. To combat this, we use a 'Disaster index' approach in line with El Ouadghiri et al. (2021). Following intuition, a natural disaster with a multitude of casualties and affected people could generate more attention than a comparable disaster that lacks that impact. The Disaster index, denoted as $DIS\ Index_t$, accounts for this. This measure is calculated as $\ln(e^1 + (\Sigma casualties_t + \Sigma affected\ people_t))$, where $\Sigma casualties_t$ and $\Sigma affected\ people_t$ refer to the aggregate of casualties and affected people in a given month *t*. Implementing the $DIS\ Index_t$ variable into Regression (2) provides a pooled linear regression model in the following form:

$$
\begin{aligned}
FLOW_{i,t} = a + \ & b_1 DIS\ Index_t + b_2 GREEN_{i,t} \\
& + b_3\left(DIS\ Index_t * GREEN_{i,t}\right) + gControls \\
& + \gamma_2 T_2 + \cdots + \gamma_n T_n + \ \delta_2 S_2 + \cdots + \delta_n T_n + e_{i,t} \qquad (3)
\end{aligned}
$$

As the *Disaster index* is constructed as a natural logarithm, the economic significance of the results as provided in Table H, in the Appendix, is not directly intuitive. Similar to our base results in Table IV, the coefficients of the interaction term with $GREEN_{i,t}$ remain positively signed, with the coefficients of the UK and Germany significant at the sub-10% level. Interestingly, those countries also provided the highest loadings in our base results, which remains the case under the new disaster measure. This shows that including the disaster magnitude takes away significance across the board, implying that a larger disaster does not consistently generate as much more attention than a separate, new disaster. With the exception of Spain, results remain positive and strongly significant when considering the normalized fund flow measure. Besides, the explanatory power of the models with the *Disaster index* is not notably higher than the models using the disaster dummy. Concluding, the results show relative robustness to a different measurement method for local disasters, however also indicating that an increased event magnitude has less effect on green fund flows than simply the occurrence of another substantial local natural disaster.

Fund fixed effects

Our base regressions already include month and Morningstar category fixed effects and clustered standard errors, while for our second robustness test, we include fund fixed effects as well. Herein we follow amongst others Ceccarelli et al. (2021), thereby accounting for potential omitted variable bias on variables that remain constant over time for any specific fund.

Table J, located in the Appendix, reflects the results of our initial core analyses, Regression (2), extended with the inclusion of fund fixed effects. As this accounts for potentially omitted variables that remain stable over time on a per-fund basis, the results consequently show considerably higher adjusted R-squared values, having increased the explanatory power of the model. The $DIS_t * GREEN_{i,t}$ independent variable shows relatively strong robustness to the inclusion of these fixed effects. Germany and France report similar net fund flow results, and considering the normalized fund flow measure, also the US and UK show robustness to the inclusion of fund fixed effects in terms of statistical significance in the positively-signed coefficients.

Other limitations

The inclusion of a magnitude-based disaster index or fund fixed effects all deal with certain methodology-specific limitations. Beyond this, certain constraints persist in our work that cannot be easily accounted for. One such restriction, inherent in the methodology we set out, relates to the time frame. Prior works on extreme weather events and disasters oftentimes took time frames of ~10-15 years (e.g. El Ouadghiri et al. (2021)), whereas our period spans 3.5 years only. This follows the introduction of the LCD label in May 2018, which as previously argued is a better differentiator for relevant green funds than other factors. That being said, the novelty of these ‘green’ labels does expose another limitation. In February 2022, Morningstar deprived a substantial amount of previously dubbed ‘sustainable’ funds of said label after reportedly discovering too ambiguous language in those funds’ filings (Quinio, 2022). This evidences that ‘green’ labels still are not bulletproof. Despite clearly being a consideration to take into account, the results in this paper are generally in line with prior research’s findings, which used other more established methods to segment green funds, accordingly providing an indication that results are not expected to be heavily affected by this.

When reviewing the results presented in our paper, another factor to consider concerns data granularity. Mutual fund flow data is presented on a monthly basis in line with prior event-focused fund flow studies by e.g. Dolvin et al. (2019), Ceccarelli et al. (2021) and Marshall et al. (2021). Additionally, the Google search volume analyses are conducted on a weekly basis to add granularity, in turn better singling out the individual effects of climate disasters on the search volume. In line with this, it can be reasonable to assume that monthly fund flow data includes noise which undermines the sole effects of the event-driven variables in our regressions. Additionally, the lack of significant results for GSVI-data as a mediator could be due to the mismatch in data granularity, as for example El Ouadghiri et al. (2021) did find significance in their study which considers weekly data on stock indices.

5 Conclusion

The analyses in this thesis find that natural disasters coincide with positive shocks in fund flows to green-labeled mutual funds within the same country as where disasters occurred. We find that those heightened flows, relative to control funds, are furthermore in line with generally increased attention towards climate change. Beyond that, our analyses provide insights into the salience effect of close-proximity events, effectively showing that despite the smaller magnitudes and generally less destructive impacts, investors value local natural disasters more in their behavioral shift towards green mutual funds.

In light of the global trend where the last seven years have been some of the warmest on record, this paper dives further into the implications that this might have on investment practices. We compare the gradual process of climate change to for instance the 'Frog in the pan' hypothesis and investigate whether experiencing extreme climate disasters provides sudden realizations of climate change severity, despite those disasters in themselves not adding to this concept. In line with that comparison, we find that local climate disasters are generally related to positive shocks in same-country search volume into climate change. Forming a proxy for investor attention, this implies that part of this attention is indeed generated spontaneously. We find that Google search volume, even through our formulated proxy of idiosyncratic search volume, somewhat surprisingly has no clear relation to mutual fund flows. Despite this missing mediating link, our findings do show that in line with heightened attention, local natural disasters relate to increased same-country targeted green fund flows. As this measure is relative to control funds, this in itself provides an indication of increased green-investment preferences at times of local disasters. Furthermore, our results point out that this effect can persist for up to three months after the first occurrence of such disasters, possibly adding to the behavioral explanation as retail investors are likely to take, or require, a longer time to act on their new realizations.

We consecutively studied the importance of event proximity, finding that in line with prior literature, close-proximity events are considered much more salient, with in turn more significant effects. Our analyses show that including a sample of the largest, most impactful climate disasters globally in the last years, has no explanatory effect on increased investor attention or green fund flows. At the same time, our findings from the local, same-country, climate disasters still hold. These results imply that the largest climate disasters, those which show most clearly the effects and extent of climate change on weather events, neither affect attention nor behavioral shifts towards green investments when those events do not occur in close proximity to the investors.

With these findings, our thesis contributes to the existing literature by adding new building blocks to research on green investment triggers, while also providing a novel link between the effects of local close-proximity events and those events that occurred in more distant locations. Namely, we show that the proximity to disasters holds considerably more weight in investment decisions than the severity of those events. Furthermore, our findings provide new insights into the lagged effect of increased green fund flows post-disaster. These implications additionally provide prominence to investors and equity analysts, in their coverage and opinions on green investment options. Specifically, they show that to some extent, the awareness of 'gradual' climate change and the subsequent adoption of green investment decisions, does not happen gradually persé, but more likely in shocks, as per our results. The findings moreover indicate that the magnitude of these shocks, as per the loadings in our regressions' coefficients, vary based on e.g. a country's size or susceptibility to climate disasters in general. Climate change, and with that extremer weather events, is likely to persist or even progress over the coming years if not decades. With that, these findings can be further substantiated over time, and their implications may very well play more important roles as time progresses.

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Appendices

Table A: Filtering Procedure

This table shows the data filtering procedure for the mutual funds data (Panel A) and the climate disaster data (Panel B). Panel A starts with all in-scope funds based on Morningstar Categories that are not limited to fixed-income or sector specific products only, for funds with the United States, Germany, the United Kingdom, France, Italy or Spain as their region of sale. Panel B starts with all natural disasters as per the EM-DAT database, since 2000. The selected disasters correspond to Table I.

Panel A: Mutual fund flow data			
Note	Share classes	% of Total	Comment
In-scope funds	67,763	100.0%	
European cross-border funds	26,550	39.2%	
Single-country targeted funds	41,213	60.8%	Excludes cross-border funds
Fund-by-region of sale level aggregates	17,559	60.8%	

Panel B: Climate disaster data			
Note	# Disasters	% of Total	Comment
Natural disasters (2000 - 2022)	9,076	100.0%	
Natural disasters (2018-05 - 2021-12)	1,451	16.0%	
Climate-related disasters	1,285	14.2%	Excludes non-climate related disaster subgroups
Selected global disasters	10	0.1%	Based on largest impact
'Local' climate disasters (2018-05 - 2021-12)	179	2.0%	Only includes US, DE, UK, FR, ES, IT-based disasters
Selected local disasters	28	0.3%	Based on largest impact

Figure A: Country-by-Country Google Search Volume for 'Global warming'

This figure shows the pooled weekly Google search volume data for the United States, Germany, the United Kingdom, France, Spain, and Italy on the topic of 'Global warming', for the the May 2018 - December 2021 period, inclusive. The data has been retrieved from Google Trends and shows the relative search volume from 0-100, in comparison to the highest search volume across the period and the pooled dataframe of all six countries combined.

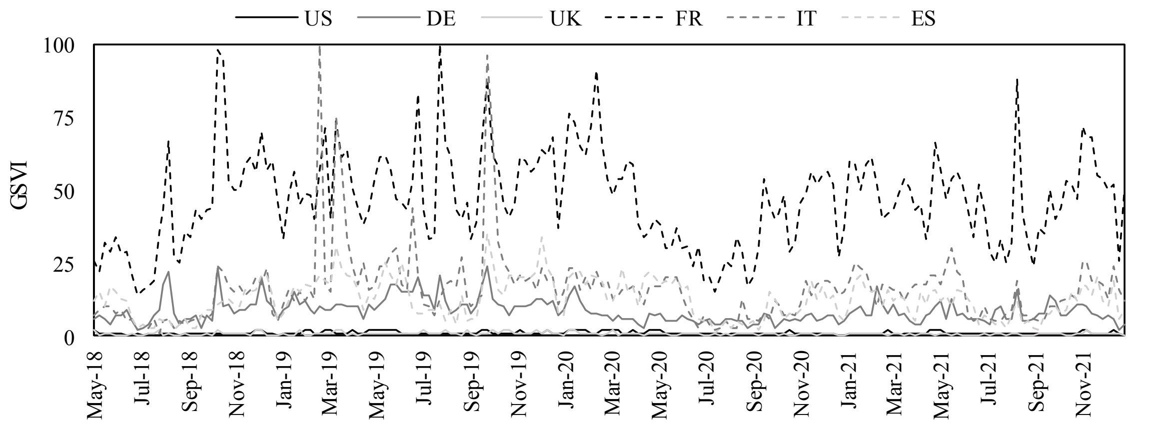

Table B: Explanatory Guidance on the Variables

This table provides detailed explanations and the primary sources for the variables as included in descriptive statistics Table II.

	Variable description	Source
FLOW	Mutual fund flows net of returns, computed as the percentage point change. Aggregated based on fund level and region of sale.	Morningstar Direct
NFLOW	Normalized mutual fund flows. Normalizes FLOW based on percentiles within total-net-asset-based deciles	Morningstar Direct
DIS	Dummy for a local climate disaster, as per Table I, occuring within a fund's region of sale in a given month	EM-DAT
GDIS	Dummy for a global climate disaster, as per Table I, occuring in a given month	EM-DAT
GREEN	Dummy for funds that obtained Morningstar's Low Carbon Designation in the latest quarterly review	Morningstar Direct
Log TNA	The natural log of a fund's total net assets	Morningstar Direct
Age	The number of years since inception of a fund's oldest underlying share class	Morningstar Direct
Log Age	The natural log of variable Age	Morningstar Direct
Volatility	The standard deviation of a funds last 12 months' monthly returns	Morningstar Direct
Return t-1	One-month lagged monthly net returns	Morningstar Direct
Globes	The Morningstar sustainability rating, ranking funds on a 1-5 scale	Morningstar Direct
Stars	The Morningstar overall rating, ranking funds on a 1-5 scale	Morningstar Direct
Δ1 Globe	Indicates whether funds entered into (1), or exited (-1), the lowest bracket of the Globes rating in the latest review	Morningstar Direct
Δ5 Globe	Indicates whether funds entered into (1), or exited (-1), the highest bracket of the Globes rating in the latest review	Morningstar Direct
ΔStars	Indicates whether funds received an upgrade (1), or downgrade (-1), for the Stars rating in the latest review	Morningstar Direct
GSVI	The natural log change in Google search volume index data for the topic 'Climate change'. GSVI values are country specific	Google Trends
GSVI adj.	Proxy for idiosyncratic GSVI data. GSVI adjusted for seasonality and the systematic movements by *Other events*, those specified in Table E	Google Trends

Table C: Geographical Segmentation of the Key Variables of Interest

This table shows the geographical distribution of the key variables of interest within our analyses, for each of the six countries at focus. The observations in each country correspond to monthly aggregated share class observations, at a fund-by-region of sale level, wherein the region of sale corresponds to the country. GREEN indicates the fraction of observations that are allocated the Morningstar Low Carbon Designation in the latest quarterly review. DIS indicates the fraction of observations that coincide with a local climate disaster as per the selection in Table I. GDIS indicates the fraction of observations that coincide with a global foreign disaster as per Table I. FLOWS statistics indicate the quartiles and standard deviations for mutual fund flows for each of the countries respectively.

					FLOWS			
Region of sale	N	GREEN	DIS	GDIS	p25	p50	p75	sd
United States	134,621	0.27	0.37	0.22	-1.23	-0.39	0.55	2.97
Germany	46,776	0.14	0.07	0.20	-0.50	0.00	0.49	2.54
United Kingdom	49,504	0.17	0.09	0.20	-0.92	-0.07	0.70	2.99
France	76,991	0.11	0.11	0.20	-0.73	-0.04	0.37	2.70
Italy	31,475	0.07	0.11	0.20	-2.01	-0.78	0.00	3.07
Spain	129,152	0.09	0.11	0.20	0.00	0.00	0.00	2.14
Total	468,519	0.16	0.18	0.21	-0.83	0.00	0.21	2.70

Table D: Pairwise Correlation Results

This table shows the pairwise correlations between the core variables' monthly aggregated observations, for the May 2018 - December 2021 period, inclusive. * indicates statistical significance at the 1% level.

		1	2	3	4	5	6	7	8	9	10	11	12
1	FLOW												
2	NFLOW	0.88*											
3	DIS	-0.01*	-0.01*										
4	GDIS	0.01*	0.00	0.17*									
5	GREEN	0.03*	0.04*	0.08*	-0.04*								
6	Log TNA	-0.03*	0.02*	0.15*	0.00	0.18*							
7	Age	-0.11*	-0.12*	0.05*	-0.01*	0.12*	0.21*						
8	Volatility	-0.02*	-0.01*	0.16*	-0.04*	0.13*	0.15*	0.13*					
9	Return t-1	0.02*	0.02*	0.03*	-0.05*	0.07*	0.07*	0.03*	0.14*				
10	Globes	0.04*	0.05*	-0.06*	-0.01*	0.20*	-0.05*	0.00	-0.12*	0.00			
11	Stars	0.16*	0.22*	0.00	0.00	0.09*	0.22*	0.00	-0.04*	0.04*	0.13*		
12	GSVI	0.00	0.00	0.16*	0.08*	-0.01*	-0.01*	-0.01*	0.00	0.03*	0.00	0.00	
13	GSVI adj.	0.00	0.00	0.08*	0.06*	0.00	0.00	0.00	0.10*	0.09*	-0.01*	0.00	0.57*

Table E: Descriptions of Selected Other Events

This table shows a number of selected other non-disaster events, which are deemed to have a systematic attention-grabbing effect within the scope of climate change. Using the search volume for the topics 'Climate change' and 'Global warming' as indication, the selected events are taken based on their attention-grabbing potential, as well as through building on prior literature by e.g. Ramelli et al (2021). As such, the data frame includes climate conferences, climate strikes and UN climate report releases within the May 2018 - December 2021 period, inclusive.

Start date	End date	Country	Event Type	Event name
08/10/2018	08/10/2018	n.a.	Release of UN Climate Report	IPCC Special Report: Global Warming of 1.5 ℃
02/12/2018	14/12/2018	Poland	Climate Conference	COP 24
15/03/2019	15/03/2019	n.a.	Climate Strike	First Global Strike
24/05/2019	24/05/2019	n.a.	Climate Strike	Second Global Strike
20/09/2019	27/09/2019	n.a.	Climate Strike	Global Week for Future
02/12/2019	13/12/2019	Spain	Climate Conference	COP 25
09/08/2021	09/08/2021	n.a.	Release of UN Climate Report	IPCC Climate Report (AR6) – First Part
31/10/2021	12/11/2021	United Kingdom	Climate Conference	COP 26

Table F: The Effect of Climate Disasters on Same-Country 'Global warming' Attention

This table shows results of OLS regressions of weekly Google search volume index ('GSVI') data, for the topic 'Global warming', on dummy variable DIS. The latter indicates the occurance of a climate disaster, as per the selection in Table I, for that given week within the model-corresponding country. The models in this table control for dummy variable OE, indicating whether one of the events as specified in Table E occurred in that given week. All models include GSVI data for the May 2018 - December 2021 period, inclusive. All regressions control for month and year fixed effects. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	GSVI 'Global warming' (weekly)					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS	0.086	0.502**	0.598	0.520***	0.194	0.219
	(0.094)	(0.201)	(0.469)	(0.118)	(0.205)	(0.180)
OE	0.311**	0.410***	0.613**	0.363***	0.622***	0.312**
	(0.135)	(0.114)	(0.278)	(0.085)	(0.149)	(0.149)
Observations	192	192	192	192	192	192
Adjusted R^2	0.00	0.06	-0.04	0.13	0.05	0.03
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table G: The Lagged Effect of Climate Disasters on Same-Country Mutual Fund Flows

This table shows results of pooled linear regression models of four-monthly net flows, on dummy variable DIS and the interaction of this variable with dummy GREEN. DIS indicates the occurance of a climate disaster, as per the selection in Table I, for the first month (out of four) for which net flows are considered within the model-corresponding country. GREEN indicates whether a fund has been allocated the Morningstar Low Carbon Designation in the latest quarterly review. All models include fund flow data for the May 2018 - December 2021 period, inclusive, thereby allowing for less observations in a quarterly analysis, as compared to a monthly analysis, due to data availability. All regressions control for month and style fixed effects, as well as clustered standard errors. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Triannual flows					
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS x GREEN	0.201*	0.480**	0.730**	0.115	0.055	0.278
	(0.101)	(0.162)	(0.296)	(0.068)	(0.567)	(0.279)
DIS	-0.367	1.623***	-0.242	0.031	-0.539	-0.020
	(0.392)	(0.147)	(0.354)	(0.211)	(0.628)	(0.312)
Observations	124,685	43,307	45,513	71,302	28,864	119,940
Adjusted R^2	0.15	0.08	0.15	0.07	0.20	0.07
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

Table H: The Effect of Climate Disasters on Same-Country Mutual Fund Flows - Robustness Test: Measured by Disaster Index

This table shows results of pooled linear regression models of monthly mutual fund flows, considered as monthly net flows (Panel A) and normalized flows (Panel B), on variable DIS Index and the interaction of this variable with dummy GREEN. DIS Index indicates the natural logged aggregate of disaster casualties and affected people, as per the disaster selection in Table I, for that given month within the model-corresponding country. GREEN indicates whether a fund has been allocated the Morningstar Low Carbon Designation in the latest quarterly review. All models include fund flow data for the May 2018 - December 2021 period, inclusive. All regressions control for month and style fixed effects, as well as clustered standard errors, and the same control variables as in Table IV. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Flows

	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS Index x GREEN	0.006	0.034*	0.059**	0.025	0.015	0.007
	(0.005)	(0.018)	(0.025)	(0.016)	(0.024)	(0.008)
DIS Index	-0.007	0.041*	-0.009	0.006	-0.017	0.009
	(0.008)	(0.022)	(0.019)	(0.011)	(0.016)	(0.009)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.09	0.04	0.09	0.04	0.15	0.03
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Normalized flows

	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS Index x GREEN	0.128***	0.384**	0.501***	0.339**	0.448***	0.040
	(0.038)	(0.169)	(0.144)	(0.139)	(0.143)	(0.074)
DIS Index	-0.096	-0.246	0.218**	-0.005	-0.288	0.119
	(0.055)	(0.197)	(0.096)	(0.135)	(0.165)	(0.067)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.12	0.07	0.11	0.05	0.19	0.05
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

Table J: The Effect of Climate Disasters on Same-Country Mutual Fund Flows - Robustness Test: Controlling for Fund Fixed Effects

This table shows results of pooled linear regression models of monthly net flows (Panel A) and monthly normalized flows (Panel B), on dummy variable DIS and the interaction of this variable with dummy GREEN. DIS indicates the occurance of a climate disaster, as per the selection in Table I, for that given month within the model-corresponding country. GREEN denotes a fund that has been allocated the Morningstar Low Carbon Designation in the latest quarterly review. All models include fund flow data for the May 2018 - December 2021 period, inclusive. All regressions control for month, style and fund fixed effects, month-by-style clustered standard errors, and the same control variables as in Table IV. Standard errors are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Flows						
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS x GREEN	0.108	0.218***	0.298	0.221**	0.117	0.043
	(0.060)	(0.049)	(0.167)	(0.084)	(0.170)	(0.073)
DIS	0.013	0.196***	-0.040	0.052	-0.120	0.027
	(0.064)	(0.042)	(0.117)	(0.095)	(0.075)	(0.033)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.25	0.21	0.30	0.17	0.35	0.16
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Normalized flows						
	(1)	(2)	(3)	(4)	(5)	(6)
	US	DE	UK	FR	IT	ES
DIS x GREEN	1.456***	2.268***	2.455**	2.496***	2.603	0.282
	(0.462)	(0.599)	(1.031)	(0.570)	(1.470)	(0.231)
DIS	-0.627*	-1.774***	1.505***	0.117	-2.000**	0.136
	(0.322)	(0.564)	(0.436)	(0.521)	(0.887)	(0.247)
Observations	134,621	46,776	49,504	76,991	31,475	129,152
Adjusted R^2	0.35	0.30	0.38	0.24	0.46	0.22
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Style Clust. SE	Yes	Yes	Yes	Yes	Yes	Yes