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Natural Disasters, Investor Attention, and Non-Fundamental Green Asset Demand

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Abstract

This study examines how the occurrence of natural disasters in the U.S. influences investor interest in green assets and actual investments, focusing on inflows into green ETFs as a proxy for non-fundamental demand. Event study analyses demonstrate both increases in investor interest in eco-friendly investments (proxied by Google searches) and inflows into green ETFs following disasters, driven by the period following the 2015 Paris Agreement. The additional inflows average about $4.3 million in the week directly following disasters, compared to average inflows of around $1.1 million in the non-disaster reference window. Importantly, both effects disappear when other attention-grabbing events, such as terrorist attacks or mass shootings, occur simultaneously with disasters. Analysis of climate change coverage across U.S. media suggests that media attention devoted to climate change concerns drives the documented shifts in investor behavior towards green investments. Furthermore, analysis of flows in brown ETFs (e.g., the oil and gas sector) reveals analogous disinvestments in the wake of disasters, but notably, only in the absence of concurrent distracting events.

Keywords: Investor attention, green investing, natural disasters, ETFs, non-fundamental demand, green sentiment, ESG, media attention, Paris Agreement

JEL classifications: G14, G41

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1 Introduction

"Achieving the United Nations' Sustainable Development Goals and Paris climate goals will require a large amount of capital (Volz and Schoenmaker, 2022). Some of this capital could potentially be provided by investors using environmental, social, and governance (ESG) criteria." (Pástor et al., 2023)

In today's era, characterized by heightened environmental awareness and the urgent need to address climate change, the concept of green[1] investments has emerged as a critical avenue for aligning financial decisions with sustainability goals. This paper investigates whether U.S. investor interest in green assets and actual investments change in the wake of natural disasters. Specifically, we focus on shifts in green preferences that cannot be attributed to changes in the fundamental values of these assets, highlighting an increase in 'green sentiment' among investors. To capture these shifts, we rely on observed flows into green-labeled exchange-traded funds (ETFs).

Moreover, we examine how attention-grabbing concurrent events that potentially distract investor attention interact with the observed patterns regarding green investing behavior. Put simply, we analyze whether the potential shift in green investing behavior following disasters gets moderated by the occurrence of other (non-climate-related) events that are likely to dominate the news and capture investors' (limited) attention.

While existing literature shows higher demand (a mix of both fundamental and non-fundamental) for green assets after disasters occur, this paper, to the best of our knowledge, is the first to explore how this effect is moderated by simultaneous attention-grabbing events. Furthermore, it is also the first paper that relates the occurrence of disasters to a clean measure of non-fundamental demand. This metric, as proposed and motivated both theoretically and empirically by Brown et al. (2021), leverages observed flows into ETFs resulting from institutional actors' arbitrage activities, which compensate for disparities between ETF and underlying asset prices. Notably, this metric has already found application in constructing a green sentiment index by Brière and Ramelli (2022) and a speculation sentiment index by Davies (2022).

Using event study designs, we uncover several findings. First, we observe a significant increase in Google search queries for environmentally friendly investments in the week following serious disaster activity across the U.S. Second, aligned with this growing interest, we observe a substantial increase in funds directed towards green-labeled ETFs during the same week. Importantly, these results are driven by the period following the 2015 Paris Agreement, characterized by generally higher levels of climate change awareness and concerns.

[1] When referring to 'green,' 'eco,' 'eco-friendly,' and 'sustainable' investing, we specifically denote investment practices that prioritize environmental considerations alongside financial metrics. In our empirical analysis, we operationalize this concept by labeling specific funds containing keywords related to environmental issues. We adopt this method under the premise that such keywords effectively convey a fund's dedication to environmentally friendly investments – in line with approaches employed in previous studies, such as in Berg et al. (2022a) and Brière and Ramelli (2022).

In terms of effect sizes, Google search queries for the topic of 'eco-investing' increase by 8.34 units in the index compared to the reference period (including weeks far outside the disaster window), which amounts to over 80% of a standard deviation in the index. Regarding changes in actual investments in green ETFs, we document an average additional influx of \$4.26 million into green ETFs compared to the non-disaster window, where green ETF flows typically stand at \$1.08 million.

However, the scenario changes drastically when disasters coincide with other significant events that likely capture investors' attention. If a terror attack, mass shooting, or technological accident (such as a plane crash) occurs in the U.S. during a disaster week, we observe no significant shifts in investor interest or actual investments into green ETFs. This suggests that investor attention is diverted by these attention-grabbing events, ultimately crowding out green investing behavior.

In an additional analysis, we explore the relationship between the occurrence of disasters and concurrent distracting events on climate change coverage across U.S. media. Here, we use an index constructed and validated by Ardia et al. (2022), which captures both coverage and expressed concerns about climate change. We document an increase in the index in the weeks following disasters, but only when disasters occur *without* other attention-grabbing events. Therefore, this additional finding supports the idea that media attention devoted to disasters and climate change debates is primarily responsible for the documented shifts in investor behavior towards green investments.

Finally, we examine whether there is analogous evidence for divestment from brown ETFs in the wake of disasters. ETFs are labeled as brown when they indicate belonging to traditional energy industries such as oil and gas sectors. We indeed find evidence consistent with investors divesting from brown ETFs while concurrently increasing their green sentiment by investing more in green ETFs. Importantly, again, these behavioral changes in response to disasters are observable only in the absence of distracting events that would otherwise crowd out attention on disasters and climate change.

The remainder of the paper is structured as follows: Section 2 reviews related literature. Section 3 discusses the relevant theoretical framework, focusing on how (media) attention to climate disasters may affect investor motivations to allocate resources into environmentally friendly assets. Following this, Section 4 introduces our empirical approach, describing the event study design that links occurrences of disasters and distracting events to the outcomes under investigation. This section also describes the data sources and elaborates on the coding of key variables used in our event study analyses. The results on changing patterns of investor interest in green investments (proxied by Google searches) and actual green ETF investments in the wake of disasters and distracting events are presented in Section 5. Complementary analyses on climate change media coverage and brown ETFs are presented in Section 6. Robustness tests are provided in Section 7. Finally, Section 8 offers concluding remarks.

2 Literature

This paper contributes to the literature on the influence of climate change events on green investment behavior, as well as studies examining the media's role in affecting investor behavior by increasing attention to climate change. These two strands of literature are closely connected, as media serve as an essential channel for investors to receive information and direct their attention, especially after climate-related disasters.

Climate Change Events and Green Investment Behavior

The impact of climate change events on the demand for green assets has been extensively studied using different methodologies and data. Marshall et al. (2021) identify a positive correlation between climate disasters and inflows into green mutual funds. This relationship increases when the disaster is associated with increased Google searches for socially responsible investing. However, their analysis of non-fundamental demand may be constrained by their reliance on mutual fund flows.[2] Choi et al. (2020) explore the effects of extreme temperature events on public beliefs about climate change, showing that warmer temperatures lead to an increase in Google searches related to climate change and prompt retail investors to divest from environmentally unfriendly 'brown' firms, which subsequently underperform. Importantly, this underperformance does not seem to be linked to fundamental changes in the firms' valuations. Similarly, El Ouadghiri et al. (2021) document higher returns for sustainable U.S. stocks following global natural disasters, while Fiordelisi et al. (2023) observe increased performance of socially responsible ETFs compared to conventional ETFs in such aftermaths.

While these studies highlight the positive impact of climate change events on green investment decisions, they do not address whether this effect is primarily driven by focused (media) attention to these events or if it would persist regardless. Investors may recognize the long-term risks associated with climate change, which could independently influence their decisions. Our study addresses this issue by examining the extent to which green investment is affected in the wake of disasters under two distinct scenarios. We compare changes in green investing when disasters occur alone versus when they coincide with other newsworthy events, such as terror attacks and mass shootings, which may distract attention from the disasters.

Media's Role in Promoting Green Investment Behavior

Numerous studies demonstrate the powerful role mass media plays in increasing public awareness about environmental issues (see, e.g., Sampei and Aoyagi-Usui, 2009).[3] According to

[2] Brown et al. (2021) argue that to effectively measure non-fundamental demand, it is necessary to address the relative mispricing between the fund and its underlying assets, and the subsequent correction of this mispricing by authorized participants, a mechanism inherent in ETFs. They suggest that metrics such as mutual fund flows and trading volume may not provide a clean measure of non-fundamental demand due to factors like investor preferences for certain fund managers, fund manager skills and the complexity of deciphering trading motives from trading volume data.

[3] See Engelberg and Parsons (2011) for well-identified evidence on the causal impact of media coverage on financial markets in the context of firm earnings announcements. In particular, the authors compare changes in

Ardia et al. (2022), media's influence on public perceptions extends beyond merely disseminating information about climate change. The authors highlight the significance of both the quantity and tone of media coverage on climate-related topics. Based on this, they develop a climate change concern index that assesses both the extent and critical nature of reporting across important U.S. newspapers. Their study demonstrates the index's robust predictive ability in discerning the performance gap between green and brown stocks. In a similar vein, El Ouadghiri et al. (2021) show that increased public attention to climate change – quantified by both media coverage and Google searches – is positively correlated with the returns of U.S. sustainability stock indices. Conversely, this increased attention has a negative impact on conventional stock indices. Finally, also using Google search data, Aliano et al. (2023) show on a global level that in times of increased public attention on climate change, stocks with higher ESG ratings achieve better returns compared to less sustainable stocks.

Despite identifying positive correlations between increased media climate coverage, heightened public attention to the topic, and green investment decisions, this research leaves the precise role of media unclear. Imagine a scenario where people become more aware of environmental issues. This heightened awareness could lead to more media coverage of climate topics but also directly affect green investment choices. To address this issue of endogeneity, empirical settings are required that can effectively isolate the impact of media coverage while holding environmental awareness constant.

Moreover, the aforementioned studies on how climate events and media climate coverage affect green investment behavior leave open the question of whether the surge in demand is driven by fundamental or non-fundamental factors. In our study, we employ a measure for non-fundamental demand, following the methodology developed by Brown et al. (2021). We thus interpret the documented changes in green investment behavior as likely reflecting investors' shifting preferences towards green investment alternatives.

3 Theoretical Framework: Motivations in Green Investing and the Role of Limited Investor Attention

Diverse factors and motivations influence investors' decisions regarding green investments. This section examines these factors, emphasizing the findings and evidence from recent studies. We also consider how these factors might interact with the occurrence of natural disasters and the role of the media in providing the information that retail investors rely on when forming their investment decisions, along with the concept of investors' limited attention. We conclude with a hypothesis suggesting that retail investors' decisions regarding green investments may be moderated by the occurrence of simultaneous events that divert attention away from natural disasters and associated climate change concerns.

investor behavior among individuals exposed to the same announcement but with access to varying levels of media coverage of it.

Fundamental vs. Non-Fundamental Motives in Green Investing

Investment motivations can broadly be categorized into two main types: those driven by new fundamental information about the fair value and performance of assets, and those not motivated by such information. Fundamental information includes financial metrics such as earnings, cash flows, and macroeconomic indicators, which are crucial for determining an asset's intrinsic value through detailed financial analysis and valuation models. Investors relying on fundamental information aim to make informed decisions based on the true economic worth and potential future performance of the assets. In contrast, non-fundamental demand can be driven by pecuniary (financial) motives like speculation and psychological biases, or by non-pecuniary (non-financial) motives such as personal preferences, and does not rely on changes in the asset's fundamental value.

Numerous studies have examined the non-pecuniary motivations behind green investments. Riedl and Smeets (2017) document that the primary reasons individuals choose to invest in socially responsible ways are social preferences and social signaling. They find that financial considerations are often secondary, as investors are willing to sacrifice some financial returns to align their investments with their social values. Similarly, Pástor et al. (2021) emphasize in their theoretical model that green investing aligns with investors' utility functions – investors gain utility when their investments meet their environmental preferences, which is why green assets have low expected returns in equilibrium.[4] In addition to social and ethical considerations in green investing, recent research emphasizes the importance of altruism and warm glow (Andreoni, 1990) in socially responsible investing. In this context, Brodback et al. (2019) provide evidence supporting a connection between investors' altruistic motives and sustainable investing strategies. Dam (2011) presents a model incorporating warm glow in green investing. In this model, investors gain a private benefit from the act of sustainable investing itself, independent of the benefit received from the public good.

As for non-fundamental pecuniary motivations in the context of green investing, investors may base their decisions on historical performance, potentially conflating high past returns with future expected returns. Green assets have demonstrated substantial growth over the past decade, with pronounced realized returns. However, investors may mistakenly associate these past high returns with expected future returns, which Pástor et al. (2022) has shown to be comparatively lower. In this context, Hartzmark and Sussman (2019) provide evidence that investors indeed view sustainability as positively associated with future performance, although they do not find evidence that high-sustainability funds outperform low-sustainability funds. Additionally, in an era characterized by environmental uncertainties, green investments may serve as strategic hedges against the risks associated with climate change and environmental degradation, as noted by Engle et al. (2020). Finally, investors may hold beliefs about the

[4] However, empirical observations suggest a different trend. Pástor et al. (2022) report that green assets have experienced high realized returns in the past years, contrary to the theoretical expectation of lower expected returns. They attribute these higher realized returns to unexpected demand shocks, likely triggered by sudden spikes in environmental concerns.

Figure 1: Fundamental vs. Non-Fundamental Motives in Green Investing

Green Asset Demand

Fundamental Demand

- Arrival of new information on fundamentals which updates asset's intrinsic value

Non-Fundamental Demand

Pecuniary Motives

- Hedging
- Active Management
- Speculation/Beliefs

Non-Pecuniary Motives

- Preferences
- Ethics/Moral
- Warm Glow

intrinsic worth of green assets, assuming that this value is not yet fully reflected in the current market price. In a current survey among U.S. retail investors (Giglio et al., 2023), it is suggested that ethical considerations, climate hedging, and return expectations all play a role in why they engage in ESG investing (with survey respondents indicating at rates of 25%, 22%, and 7%, respectively, that these are the primary reasons for their ESG investments).

Figure 1 provides an overview of motivations associated with this broad categorization regarding green investing. In the scope of our study, we aim to understand the changing investment patterns of investors in the wake of natural disasters as such that are not influenced by changes in fundamental asset values – often referred to as 'investor sentiment'. Baker and Wurgler (2007) define investor sentiment as "the belief about future cash flows and investment risks that is not justified by the facts at hand." Therefore, in our empirical investigation (see Section 4), we rely on a measure that captures solely changes in investors' non-fundamental demand for green assets: following the methodology proposed by Brown et al. (2021), we analyze the in- and outflows from green-labeled ETFs in the primary market. This approach enables us to disentangle shifts in investor sentiment towards green assets while controlling for any fundamental changes in the valuations of these investments. However, it does not allow us to distinguish whether the observed patterns are driven by pecuniary or non-pecuniary motives.

The Role of Investor (In)attention in Green Investing

The concept of rational inattention (Sims, 2003) suggests that with the overwhelming amount of information available today, investors cannot possibly process everything but will selectively focus on what they perceive as most relevant (see Maćkowiak et al., 2023 for a review on the literature on rational inattention). For example, retail investors might skim through social media or news channels, pausing only at items that catch their interest. This means that if certain topics are not prominently featured in the media or receive attention through other means, they may not influence investor behavior. Seasholes and Wu (2007), Barber and Odean (2008), and Engelberg and Parsons (2011) provide evidence for this hypothesis, showing that retail investors exhibit heightened demand for attention-grabbing stocks (those with abnormal returns, volume, or media coverage). Importantly, as shown by Barber and Odean (2008), this behavior does not apply to institutional investors. As professionals with greater resources, institutional investors dedicate more time to continuous research and market monitoring, making more informed investment decisions.

With investor attention being a key driver of whether certain information is processed, the timing of information releases becomes very relevant. This is underscored by DellaVigna and Pollet (2009), who document that investor responses to Friday earnings announcements are significantly lower than to those made on other weekdays. Similarly, Hirshleifer et al. (2009) find that investor information processing slows down when multiple announcements are made on the same day, likely diluting attention to individual events.

Given the occurrence of climate-related disasters, increases in investments in greener firms might happen for two main reasons. On the one hand, this may occur because institutional investors value greener firms higher after disasters due to their long-term sustainability practices, which increase resilience and stability in a volatile environment. On the other hand, media coverage of climate disasters may act as an exogenous stimulus, directing retail investors' attention towards climate change and associated challenges.[5] Therefore, the occurrence of climate disasters could lead investors to turn to more sustainable investments for reasons beyond mere changes in the fundamental valuations of green firms, which we summarize as expressions of green sentiment. Our empirical test focuses in particular on these non-fundamentally driven changes in green investments in the wake of climate disasters.

With retail investors' limited attention spans, we expect the latter effect only to occur if investors also pay attention to disasters and the ongoing debates in the media or social networks. Thus, we hypothesize that we will not observe the same non-fundamentally motivated increase in green investments when other newsworthy events occur alongside disasters, which distract attention away from them, compared to when disasters occur in isolation.

In order to test this hypothesis, we link the occurrence of natural disasters across the U.S. to i) shifts in investor interest towards eco-friendly investment strategies (using Google search data), and ii) shifts in investors' non-fundamentally driven investment decisions regarding green assets. The following section outlines the empirical strategy employed to examine these relationships.

4 Empirical Model and Data

This section presents the data and econometric specifications used for identifying the impact of climate disasters and concurrent attention-grabbing events on investor behavior. First, we introduce the event study design and the econometric models used, followed by a description of the data sources and the coding of the variables.

[5]Besides these short-term effects of increased attention to climate change in the wake of disasters, the media also plays an important role on a more general level in directing green investments – for example, by emphasizing the consequences of climate change, informing about green finance alternatives and their potential future returns, and advocating for action (see Weingart et al., 2000).

4.1 Event Study Design

Our empirical strategy involves employing an event study design to estimate how the outcomes on investor intentions and behavior evolve around the occurrence of disasters and concurrent events. Specifically, we examine investors' intentions to engage in green investing and actual investments in green ETFs. Regarding investment intentions, we rely on Google searches on topics related to green investing by estimating variants of the following econometric equation:

$$
\begin{aligned}
\textit{Google Searches Eco-Investing}_t = & \sum_{j=\underline{j}}^{\bar{j}} \beta_j \times \textit{Disaster}_{t-j} \\
& + \sum_{j=\underline{j}}^{\bar{j}} \gamma_j \times \textit{Concurrent Event}_{t-j} \\
& + \sum_{j=\underline{j}}^{\bar{j}} \delta_j \times \textit{Disaster}_{t-j} \times \textit{Concurrent Event}_{t-j} \\
& + \textit{Month-by-Year}_t \; FE + \epsilon_t.
\end{aligned} \tag{1}
$$

In this equation, the dependent variable captures Google search queries for green investing strategies (further explained below) in a specific week t. The *Disaster* dummy variables capture the effects of disasters at various time leads and lags (denoted by j, taking on negative and positive numbers) before and after a specific disaster week, including the week of the disaster itself. Similarly, the *Concurrent Event* dummy variables capture the effect of potentially distracting events (terror attacks, mass shootings, technological accidents) in the weeks around when such an event occurs. The interaction between the two, *Disaster* $\times$ *Concurrent Event*, captures the differential effect when a concurrent event takes place simultaneously in a week of disaster activity.

Additionally, we include month-by-year fixed effects in our model to control for general time trends and extreme outliers in the outcome variable (such as those observed during periods of heightened environmental concerns like during a global climate summit or conference). Thus, identification of effects in this estimation model is based on the variation in the occurrence of disasters and concurrent events within particular months. To prevent collinearity issues between the leads and lags and individual months (which would occur if disasters always occurred precisely in a certain month), we run variations of the model with different numbers of leads and lags as robustness tests (see Table 6). Since the residuals, ϵ_t, might not be independent of each other within a particular time period, we cluster the heteroscedasticity-robust standard errors at the quarterly level.

After exploring the impact on investment intentions, we aim to investigate the actual impact on green investment flows in the wake of disasters. To examine this relationship, we employ the following model:

$$
\begin{aligned}
\textit{Green ETF Flows}_{i,t} = &\sum_{j=\underline{j}}^{\bar{j}} \beta_j \times \textit{Disaster}_{t-j} \\
&+ \sum_{j=\underline{j}}^{\bar{j}} \gamma_j \times \textit{Concurrent Event}_{t-j} \\
&+ \sum_{j=\underline{j}}^{\bar{j}} \delta_j \times \textit{Disaster}_{t-j} \times \textit{Concurrent Event}_{t-j} \\
&+ \textit{Month-by-Year}_t \; FE \\
&+ ETF_i \; FE + \epsilon_{i,t}.
\end{aligned} \tag{2}
$$

The dependent variable of this equation represents investments in a specific green-labeled ETF i during a particular week t, measured in \$ million (further elaborated below). These investments are explained by the previously introduced leads and lags of disasters and concurrent events. In contrast to the Google search model (1), where only one time series is analyzed, this model explains flows into various individual ETFs observed over time. In addition to controlling for month-by-year fixed effects, we include ETF-specific fixed effects in the model to account for the inherent differences in investment flows between different ETFs (or those issued by specific investment firms). This approach allows us to identify changes in investments within particular green ETFs in the wake of disasters and concurrent events, while also accounting for general trends and months with unusually high or low levels of green investment. Instances of increased green investing could, for example, coincide with periods of heightened climate change awareness, such as when there are regulatory changes supporting renewable energy or when there is generally positive media coverage on environmental issues. For this model, we use two-way clustered heteroscedasticity robust standard errors. In addition to the temporal correlations of the observations, it is plausible to assume that within a given ETF the residuals are not independent of each other.

4.2 Coding of Main Variables

In the following, we describe the coding of variables and utilized data sources used in the econometric models (1) and (2) outlined above.

Google Searches Eco-Investing In order to proxy investors' intentions to engage in green investing, we use Google search volume data.[6] Google Trends allows to explore how frequently a specific term is entered into Google's search engine over a given period, relative to overall searches on Google in that period. In addition to individual keywords, it is also possible to

[6]See www.google.com/trends.

obtain search results that are assigned to a specific topic. Topics summarize search queries that relate to the same concept, including variations in wording and language. This avoids overlooking relevant data that might be formulated differently by different users. A topic in Google Trends includes a group of related search terms in different languages within the same region (in our case, the United States), which captures general interest in a broader concept rather than just specific words. Since it is difficult to determine which term retail investors would be more likely to use to search for green investing, we rely on searches related to the topic of 'eco-investing', including searches related to keywords such as 'green investment', 'green funds', 'green finance', or variations thereof, regardless of the language used.[7]

To ensure weekly data granularity, the search volume data was divided into three subperiods, each covering five years: 2005-2009, 2010-2014, and 2015-2019. This division was necessary because Google Trends allows for weekly data extraction only within five-year intervals. Google furthermore indexes and normalizes its search queries, which means that the data:[8]

1. Is drawn from a random, unbiased sample of Google searches, indexed from 1 to 100, with 100 indicating the peak search interest for the selected time and location.
2. Reflects relative search interest, not absolute search numbers, as it is normalized against the total search volume at that time and location.

Due to this indexing and normalization, interpreting the absolute numbers can be challenging. However, our interest lies in identifying spikes in search interest for the topic 'eco-investing' over time, particularly in relation to natural disaster events, rather than the absolute number of searches. Therefore, despite the limitations in direct interpretability, the Google Trends data remains useful for our analysis. We combine the search volume data from each sub-period and convert the weekly format to match the weekly format we observe in the ETF flow data (which is aggregated from each Thursday through Wednesday).

Green ETF Flows We approximate non-fundamental shifts in investor demand for green assets by examining ETF flows in the primary market. These fund flows are a good proxy for catching demand shifts that are not based on any change in the fundamental value of the underlying assets (following the approach suggested by Brown et al., 2021).

The operational principle of an ETF is based on the concept of a basket comprising a set of assets, with both the ETF shares and the underlying assets being traded independently on the secondary market. Ideally, the ETF and the underlying assets would share the same price, reflecting the same fundamental value. However, also market forces, namely supply and demand, influence the price of the ETF and the price of the underlying assets. When a

[7]This ensures comprehensive inclusion of all languages used for searches related to the topic 'eco-investing' within the United States, preventing any potential bias towards a single language group. For instance, approximately 13% (www.census.gov) of the U.S. population speaks Spanish, and our dataset includes searches in Spanish, Chinese, and other languages, providing an accurate representation of overall interest in the topic.

[8]This information is obtained from the Google News Initiative (www.newsinitiative.withgoogle.com/resources/trainings/basics-of-google-trends).

demand shock affects the market, these two prices can diverge, leading to a relative mispricing between the ETF share and the underlying assets. The assumption as to why the ETF is more affected by the demand shock than the underlying assets is based on the different ownership structures of these two types of investment options: ETFs are mainly owned by retail investors, whereas the underlying assets are mainly owned by institutional investors (Brière and Ramelli, 2022; Ben-David et al., 2018; Brown et al., 2021). This can be attributed to the fact that ETFs offer cheaper diversification options for retail investors, as they can purchase shares of a basket (an ETF) that already contains various assets. Furthermore, the demand for ETFs, since mainly driven by retail investors, is assumed to be more prone to uninformed trading and speculative demand compared to the ETF's underlying assets (Davies, 2022). This makes ETFs more sensitive to non-fundamental demand shocks.

In the event of a positive demand shock, the price of the ETF will increase to a greater extent than the price of the underlying assets, for the reasons set out above. Consequently, there will be a relative mispricing between the two. This creates an opportunity for market arbitrageurs to gain financial profits from the price difference. The excess demand for the ETF in the secondary market results in a shortage of ETF shares. Consequently, the arbitrageur is required to purchase the underlying assets in the secondary market and deliver them to the ETF provider, with the objective of incorporating these assets into new ETF shares and thereby increasing the supply of ETF shares in the primary market. The demand for the underlying assets increases their price, while the supply of new ETF shares in the market decreases the price of the ETF until the ETF price and the price of the underlying assets converge. Eventually, the prices equalize at a new price level, which does however not necessarily reflect the fundamental value of the ETF and the underlying assets. In the event of a negative demand shock, the aforementioned mechanism is reversed. Arbitrageurs purchase ETF shares at a lower price, bring them to the ETF provider who subsequently redeems them, and sell the underlying assets at a higher price. This creation and redemption process of ETF shares creates observable money flows in the primary market. Brown et al. (2021) have shown theoretically and empirically that these flows can be used as a proxy for non-fundamental demand.

Alternatively, identifying non-fundamental demand through stock prices is challenging because fundamental values are not directly observable. Additionally, trading volumes do not reveal the motivations behind trades, while mutual fund flows add another layer of complexity as they also include information about fund manager skills, making it difficult to isolate non-fundamental demand (Brown et al., 2021).

We source the ETF flow data from Eikon/Datastream.[9] We use weekly flow data spanning the period from 2005 to 2020, excluding the disruptive COVID period (since the media coverage on COVID could itself be regarded as a confounding event and had different levels of intensified media portrayal during that period), and focus exclusively on ETFs domiciled within the United States.

[9]See https://eikon.refinitiv.com.

The identification of 'green' ETFs relies on a keyword-based approach, following the methodology used by, e.g., Brière and Ramelli (2022) and Berg et al. (2022a).[10] We define green ETFs as those that contain any of the following keywords in their asset name: 'ESG', 'green', 'sustainable', 'ecological', 'eco', 'clean', 'renewable', 'low carbon', 'climate', 'bio', 'ethical', 'responsible', 'recycle', 'solar', 'environment', 'wind', 'progressive energy', and 'SRI'. In total, the sample consists of 2512 ETFs, with 3% of them labeled as 'green' (76 ETFs). This translates to a total of 14,430 observations for the main analysis, where we track green ETF flows at the fund-week level.

Figure 2 shows the evolution of the share of green ETFs as a proportion of total ETFs over time. We observe a stark increase in green ETF investment options, particularly noticeable from the year 2015 onward. This increase likely reflects the heightened climate awareness and attention to green investment strategies following the 2015 Paris Agreement on climate change (see Fahmy, 2022 for evidence on how attention to green investments rises following the Paris Agreement). Therefore, regarding the analyses on green investing behavior, we conduct regressions separately for the two distinct periods from 2005 to 2014 and from 2015 to 2020. This approach allows us to account for potential structural breaks in investor behavior in response to disasters and concurrent events during these two observation periods.

In our baseline analysis, we focus exclusively on equity ETFs because their underlying assets are liquid compared to certain commodities, ensuring a consistent time frame for the creation and redemption process. As a robustness test, we also include bond and alternative ETFs in our analysis.[11]

Natural Disasters In order to code periods of natural disasters occurring in the United States, we use the Emergency Events Database (EM-DAT) (Guha-Sapir et al., 2015).[12] EM-DAT is a globally recognized database known for its meticulous cataloging and documentation of various disasters, including a comprehensive categorization of events as 'natural disasters'.

Within the EM-DAT database, natural disasters are categorized based on a thorough documentation process, with events originating from natural phenomena like earthquakes, floods, hurricanes, tsunamis, volcanic eruptions, and severe weather conditions. Our paper strictly adheres to the EM-DAT classification standards, ensuring the precise identification and analysis of natural disaster events. EM-DAT reports a disaster if one or more of the following criteria are met: i) ten or more fatalities; ii) 100 or more people affected; iii) declaration of a state of emergency; iv) call for international assistance.

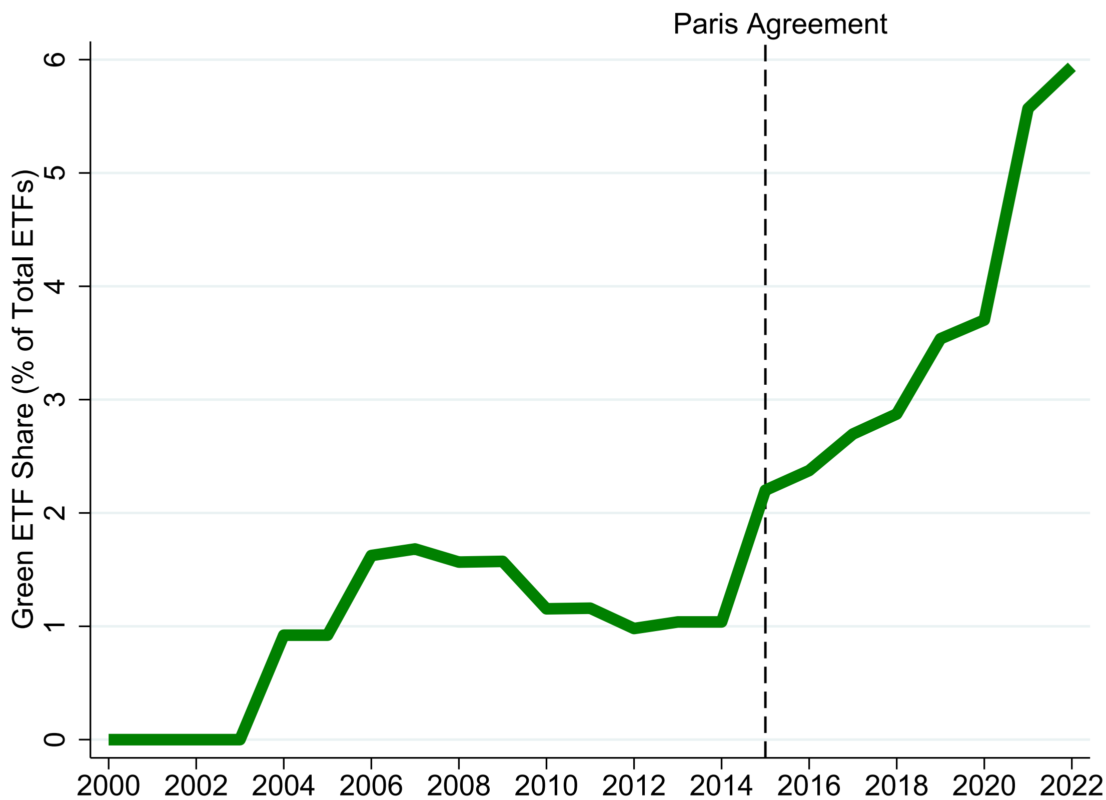
Our study focuses specifically on natural disasters with defined start and end dates that occurred solely within the United States. Disasters lacking exact start or end dates or having indefinite durations are excluded. Additionally, we restrict our analysis to disasters lasting

[10]One reason for not using ESG scores is the large heterogeneity between the ESG scores of the various rating agencies, as documented by Berg et al. (2022b).

[11]In preview, the inclusion of bond and alternative ETFs does not influence the significance or interpretation of our findings – see columns (2) and (3) of Table 8.

[12]The data are accessible through `www.emdat.be`.

Figure 2: Evolution of Green ETF Share Over Time



Notes: The graph illustrates the evolution of the share of green-labeled ETFs over time, expressed as a percentage of the total ETFs in our sample (all kind of ETFs).

a maximum of 3 days. This criterion aims to effectively assign disasters and their relevant periods of high attention to particular weeks, thereby reducing potential noise associated with longer-lasting events.[13]

To quantify the impact of these disasters, we calculate the average daily number of deaths for each event, assuming a uniform distribution of fatalities throughout the duration of the disaster – following the approach used in Balles et al. (2024). We then aggregate these daily average death counts into a weekly format to align with the ETF flow data. In cases where a disaster spans two observation weeks, we allocate the daily average number of deaths proportionally to the relevant observation weeks based on the duration of overlap. This ensures a fair distribution of fatalities across the relevant observation periods. For each observed week in our sample, we sum the number of disaster-related deaths from all natural disaster events occurring in that specific week.

[13] We thereby capture 48% of all U.S. natural disasters covered in the raw data.

To ensure that we capture weeks with significant disaster activity and notable media attention, we focus on the top 25% of weeks in the distribution of disaster-related deaths. This includes weeks with 0.5 or more deaths caused by disasters, resulting in a total of 115 out of 787 weeks considered as 'treated'. The vast majority of the 154 disasters in the ETF sample period (2005-2020) are storms and floods (95.5%), followed by wildfires at 2.6%. The remaining events include two extreme temperature events and one landslide. Importantly, all of these events can be linked to climate change, which is likely to lead to discussions about climate change in the media potentially affecting green sentiment among investors.

Concurrent Events To identify periods when attention to natural disasters and climate change is likely being crowded out, we use data on U.S. terror attacks, mass shootings, and technological accidents (such as plane crashes, explosions, or oil spills).[14] The terrorism data is drawn from the Global Terrorism Database (GTD), as introduced by LaFree and Dugan (2007). Mass shooting information is sourced from the Violence Project's mass shooter database.[15] Data on technological accidents is obtained from EM-DAT, the source that covers natural disasters as well.

These three event types are particularly suitable for our analysis because they are exogenously unpredictable and not influenced by anticipation effects, unlike planned media-intensive events such as elections or major sports events. Importantly, these events are highly attention-grabbing and likely to divert attention from natural disasters and climate change discussions when they happen at the same time, which would otherwise dominate the media.

Specifically, we identify weeks of potential distraction if a terror attack, mass shooting, or technological accident (resulting in fatalities) occurs during a week with disaster activity. In total, we have 73 weeks with terror activity, 77 weeks with mass shootings, and 45 weeks with technological accidents within the 2005-2020 sample period.[16] Overall, there are 167 weeks where at least one of the three events occurred. Among the 787 weeks in our sample, we observe 24 weeks (approximately 3%) where both disasters and concurrent events take place.

5 Results on Green Investing Intentions and Behavior

This section presents the event study findings on the impact of natural disasters and concurrent events on the two specified outcomes on investor behavior regarding green investments.

[14] The idea that attention to respectively coverage of certain events can be crowded out by concurrent events was pioneered by Eisensee and Strömberg (2007). In the context of the U.S. government's decisions to grant foreign aid money to countries affected by natural disasters, the authors estimate the effect of these events being covered by U.S. media on foreign aid decisions. The latter effects are identified by the general availability of other newsworthy material during the times of disasters, summarized in their 'daily news pressure' indicator, as well as the occurrence of major sporting events like the Olympic Games.

[15] https://www.theviolenceproject.org/mass-shooter-database; accessed November 20, 2023.

[16] Note that the terrorism data we use is available only until 2019.

5.1 Google Searches for Eco-Investing

Table 1 presents the regression results for model equation (1). In column (1), we present the estimation results when regressing Google searches on the topic 'eco-investing' on varying disaster leads and lags alone, while column (2) includes the concurrent event variable and the respective interaction terms. Columns (3) and (4) then split the sample into the pre- and post-2015 Paris Agreement periods, respectively. All variables are indexed with respect to time, starting with the lead variables $(t + 2)$, which refer to the two weeks before the event, and ending with the lag variables $(t - 4)$, which correspond to the fourth week after the event occurred. If a variable lacks a time notation, it refers to the week in which the event took place. The reference period in this setting includes all weeks lying outside the defined disaster window, comprising weeks more than two weeks before and more than four weeks after disasters.

The results indicate a pronounced and significant increase in Google searches for eco-investing in the week following disasters, especially notable during the 2015-2019 period. As noted in the data section, interpreting the effect size can be challenging; however, according to specification (4), the results suggest an average increase of 8.34 points in the index, representing 84% of a standard deviation and thus considered a relatively large effect. Additionally, for the post-Paris Agreement period starting from 2015, we observe significant increases in Google search activity for eco-investing during the week of disasters and the second week afterward. Interestingly, for this period, we already observe an uptick two weeks before weeks with disaster activity. While this could be plausible due to potential anticipation effects of disasters (predominantly storms and floods, which are somewhat predictable), we exercise caution in interpreting this increase, as it is not consistently robust in the preview of results from a robustness test, where we add more leads to the model (see, in particular, column (2) of Table 6).

Importantly, when attention-grabbing events coincide with disasters in the same week, the positive increase in searches for green investments weakens, as indicated by the negative coefficients of the corresponding interaction terms. In such a situation, where both disasters and distracting events occur, the change in searches for eco-friendly investments is calculated by adding the main effect of the disaster indicator and its interaction with the concurrent event indicator. Specifically, for the 2015-2019 period in model (4), in the week immediately following both a disaster and a distracting event, we observe a decrease in Google searches of $8.34 - 12.7 = -4.36$ units compared to the reference period.

Figure 3 shows the related event study graphs for the 2015-2019 post-Paris Agreement period, illustrating changes in Google searches following disasters, both when only disasters occur and when distracting events also coincide, with corresponding significance levels shown by the confidence intervals. When a distracting event occurs alongside a disaster, there is not an increase but rather a significant decrease in Google searches for eco-investing in the week following these events (and no significant changes for all other weeks). This finding aligns with the explanation that while retail investors typically exhibit increased interest in green investments after disasters, their attention diminishes when concurrent attention-grabbing events occur, diverting focus from disasters and climate discussions.

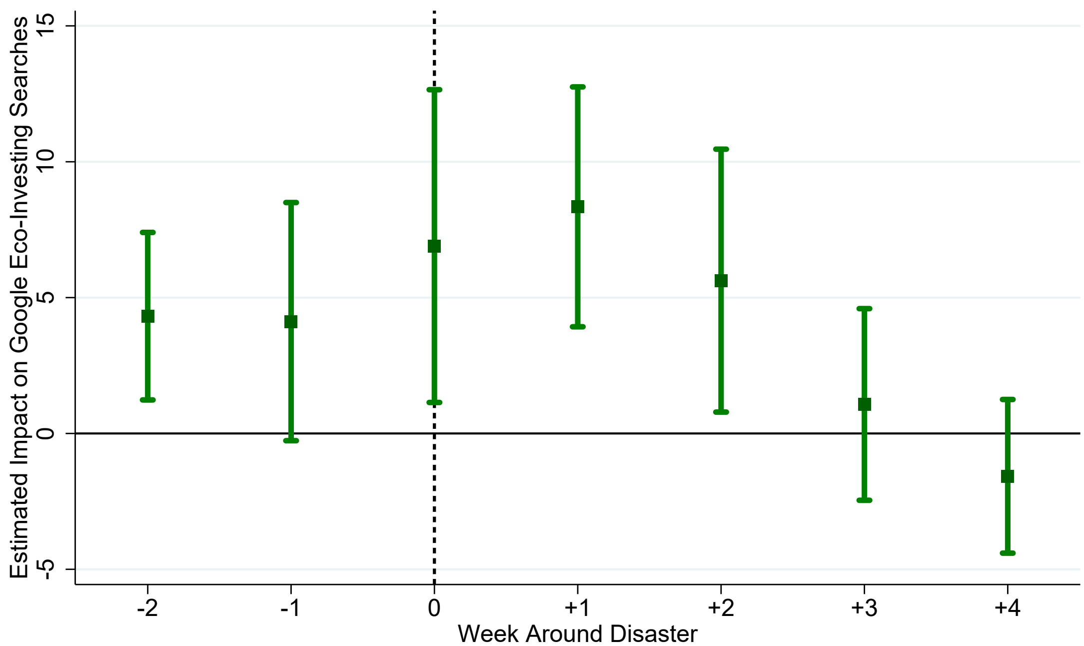
Table 1: Disasters, Concurrent Events, and Google Searches for Eco-Investing, 2005-2019

Dependent Variable: *Google Searches 'Eco-Investing'*	(1) disasters only	(2) +distraction	(3) 2005-2014	(4) 2015-2019
Disaster_{t+2}	2.178	2.922	3.454	4.316**
	(1.593)	(1.888)	(2.709)	(1.874)
Disaster_{t+1}	1.160	2.381	2.046	4.116
	(1.727)	(2.226)	(2.824)	(2.664)
Disaster_{t}	0.719	1.353	-0.322	6.896*
	(1.677)	(1.965)	(2.412)	(3.499)
Disaster_{t-1}	4.206***	5.482***	4.183*	8.340***
	(1.399)	(1.784)	(2.131)	(2.683)
Disaster_{t-2}	1.360	2.168	0.461	5.624*
	(1.598)	(1.922)	(2.511)	(2.941)
Disaster_{t-3}	-1.091	-1.205	-2.172	1.067
	(1.777)	(2.189)	(3.279)	(2.144)
Disaster_{t-4}	0.349	0.403	1.120	-1.578
	(1.271)	(1.467)	(2.013)	(1.719)
$\text{Concurrent Event}_{t+2}$		0.579	-0.269	1.909
		(1.529)	(2.509)	(1.224)
$\text{Concurrent Event}_{t+1}$		0.723	1.350	-0.272
		(2.135)	(3.299)	(2.001)
$\text{Concurrent Event}_{t}$		-1.018	-2.546	0.632
		(1.912)	(2.780)	(2.162)
$\text{Concurrent Event}_{t-1}$		0.299	-2.650	2.755
		(1.852)	(3.053)	(2.541)
$\text{Concurrent Event}_{t-2}$		0.507	-1.781	1.724
		(1.795)	(3.451)	(2.207)
$\text{Concurrent Event}_{t-3}$		-1.659	-3.547	-0.035
		(2.062)	(3.490)	(2.298)
$\text{Concurrent Event}_{t-4}$		-1.448	-1.923	-1.029
		(1.599)	(2.570)	(1.825)
$\text{Disaster x Concurrent Event}_{t+2}$		-2.681	-2.452	-6.428**
		(2.644)	(4.217)	(3.052)
$\text{Disaster x Concurrent Event}_{t+1}$		-4.493	-5.979	-4.474
		(3.670)	(4.995)	(5.338)
$\text{Disaster x Concurrent Event}_{t}$		-1.842	-0.102	-7.307
		(2.836)	(3.859)	(5.448)
$\text{Disaster x Concurrent Event}_{t-1}$		-5.507	-1.621	-12.70***
		(3.591)	(5.517)	(4.257)
$\text{Disaster x Concurrent Event}_{t-2}$		-3.176	0.868	-9.185*
		(3.964)	(6.158)	(4.507)
$\text{Disaster x Concurrent Event}_{t-3}$		1.399	3.397	-2.457
		(4.189)	(6.113)	(3.842)
$\text{Disaster x Concurrent Event}_{t-4}$		-0.424	-1.233	1.296
		(2.733)	(3.781)	(2.866)
Month-by-Year FEs	X	X	X	X
Observations	782	782	522	260
Adjusted R^2	0.226	0.216	0.206	0.155

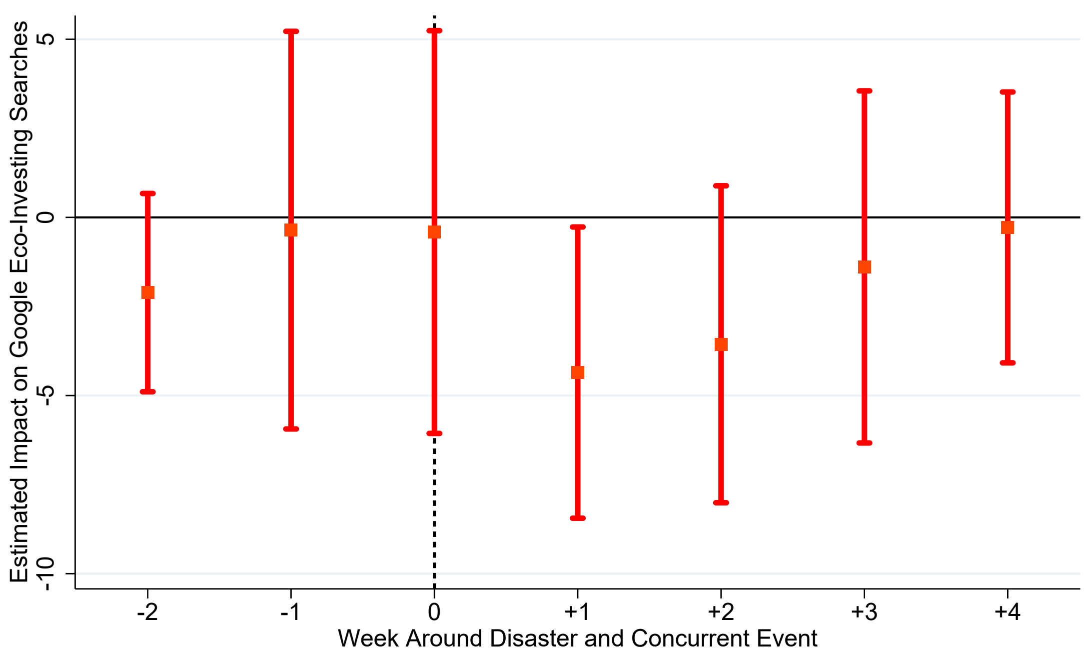
Notes: OLS regressions with robust standard errors clustered by quarter shown in parentheses. The unit of observation is a particular week. The dependent variable is the Google search index for the topic of 'eco-investing', with a mean value of 5.618 and a standard deviation of 12.63 (3.285 / 9.941 for the 2015-2019 period). Significance levels are denoted as follows: * for $p<0.1$, ** for $p<0.05$, and *** for $p<0.01$.

Figure 3: Event Study Results – Disasters, Concurrent Events, and Google Searches for Eco-Investing, 2015-2019

(a) Without Concurrent Event



(b) With Concurrent Event (Terror, Mass Shooting, or Accident)



Notes: Panel (a) illustrates the changes in Google searches related to the topic of 'eco-investing' in the wake U.S. natural disasters, without the occurrence of concurrent distracting events. Panel (b) presents the corresponding effects observed when concurrent events (terror attacks, mass shootings, or technological accidents) occur simultaneously. The related estimation results can be found in column (4) of Table 1. Both panels include 90% confidence intervals.

5.2 Green ETF Flows

Table 3 presents the event study estimation results for model equation (2) (descriptive statistics for the variables used can be found in Table 2). Column (1) shows the results when regressing green ETF flows on disaster leads and lags alone, while column (2) includes concurrent events and their interaction terms. Columns (3) and (4) respectively focus on the older period from 2005-2014 and the newer post-Paris Agreement period from 2015-2020.

The findings indicate no significant change in green ETF flows during the two weeks before a disaster or in the week of disaster activity itself. However, there is a notable effect in the week following the disaster. In specification (4) for the post-Paris Agreement period, flows into green ETFs increase by an average of $4.26 million compared to the reference period (encompassing the period more than two weeks before and more than four weeks after disasters). This effect is substantial considering mean green ETF inflows of approximately $1.22 million across the whole sample and $1.08 million during the reference period for the 2015-2020 observation period. Importantly, when examining the results solely for the older pre-Paris Agreement period 2005-2014, we do not observe significant changes in green ETF investment patterns in the wake of disasters.

Regarding the significant increases in green ETF flows in the week following serious disaster activity observed in the post-Paris Agreement period, these effects are no longer observed when additional attention-grabbing events occur in the disaster week. The related interaction term amounts to -4.44, fully offsetting the positive disaster effect. Figure 4 illustrates the event study results, depicting changes in green ETF flows around disaster weeks, both with only disaster activity and with additional distracting events. When both disasters and concurrent events occur, flows into green ETFs around disasters do not change significantly compared to those observed in the reference period. Only in the absence of distraction, we document an increase in green ETF flows in the week following disasters.

Importantly, we do not observe changes in green ETF flows following the concurrent events used to identify attention effects. This validates their use as a measure for exogenously diverting attention away from disasters.

Table 2: Descriptive Statistics for Variables in Green ETF Flows Analysis

Variable	Mean	Std. dev.	Min.	Max.	N
Green ETF Flows	1.221	26.69	-924.1	1582	14,430
Disaster	0.144	0.351	0	1	14,430
Concurrent Event	0.258	0.438	0	1	14,430
Disaster x Concurrent Event	0.031	0.172	0	1	14,430

Notes: ETF fund flows are observed at the weekly level and expressed in $mn.

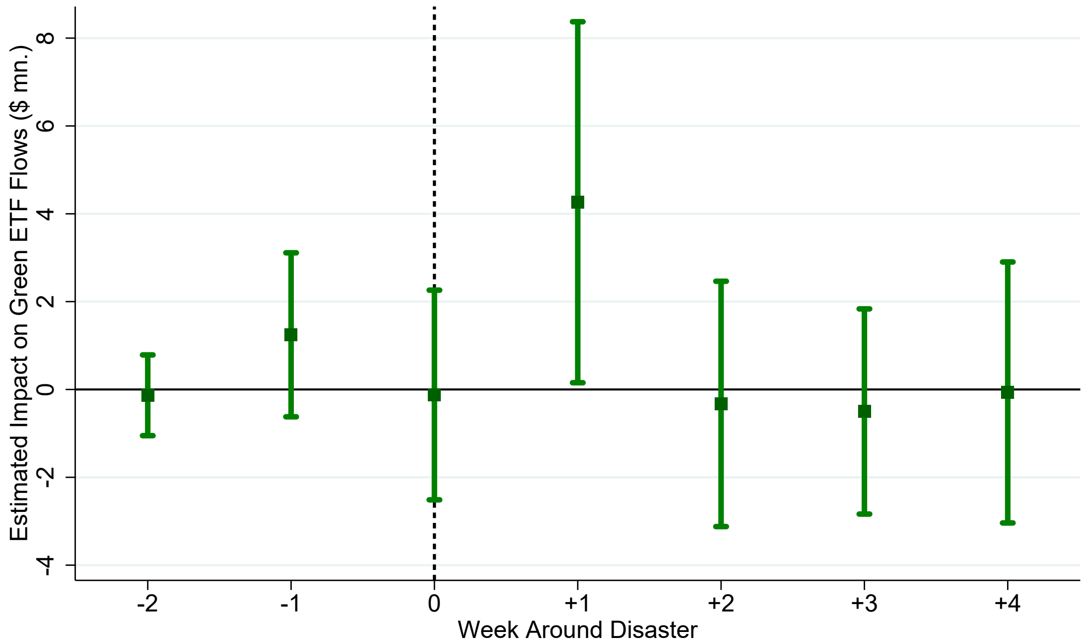
Table 3: Disasters, Concurrent Events, and Green ETF Flows, 2005-2020

Dependent Variable: *Green ETF Flows*	(1) disasters only	(2) +distraction	(3) 2005-2014	(4) 2015-2020
Disaster_{t+2}	1.082	1.460	3.310	-0.133
	(1.319)	(1.652)	(3.478)	(0.559)
Disaster_{t+1}	1.198	1.718	2.767	1.245
	(1.102)	(1.459)	(2.958)	(1.135)
Disaster_{t}	0.740	1.175	3.213	-0.126
	(1.415)	(1.760)	(3.376)	(1.451)
Disaster_{t-1}	3.489*	4.405*	5.448	4.263*
	(1.888)	(2.364)	(5.157)	(2.498)
Disaster_{t-2}	1.513	1.173	4.684	-0.329
	(1.439)	(1.825)	(4.588)	(1.698)
Disaster_{t-3}	0.253	0.475	3.015	-0.501
	(1.312)	(1.352)	(2.871)	(1.420)
Disaster_{t-4}	0.242	-0.258	0.309	-0.068
	(0.898)	(1.113)	(0.730)	(1.806)
$\text{Concurrent Event}_{t+2}$		-0.554	-1.064	-0.788
		(0.562)	(1.156)	(0.781)
$\text{Concurrent Event}_{t+1}$		-0.437	-0.017	-0.776
		(0.579)	(0.543)	(0.798)
$\text{Concurrent Event}_{t}$		0.071	1.718	-0.550
		(0.434)	(1.534)	(0.680)
$\text{Concurrent Event}_{t-1}$		0.058	2.526	-0.514
		(0.479)	(2.050)	(0.451)
$\text{Concurrent Event}_{t-2}$		-0.323	2.527	-1.120
		(0.736)	(1.967)	(0.906)
$\text{Concurrent Event}_{t-3}$		0.758	1.480	0.761
		(0.647)	(1.304)	(0.751)
$\text{Concurrent Event}_{t-4}$		-1.023	-0.281	-1.095
		(0.644)	(0.484)	(0.840)
$\text{Disaster x Concurrent Event}_{t+2}$		-0.603	0.271	0.372
		(1.329)	(1.001)	(1.525)
$\text{Disaster x Concurrent Event}_{t+1}$		-1.431	1.264	-1.656
		(1.566)	(1.605)	(1.755)
$\text{Disaster x Concurrent Event}_{t}$		-1.510	-1.492	-0.784
		(1.630)	(1.737)	(1.569)
$\text{Disaster x Concurrent Event}_{t-1}$		-3.967*	-2.031	-4.444
		(2.090)	(1.844)	(2.670)
$\text{Disaster x Concurrent Event}_{t-2}$		0.761	-2.032	1.914
		(2.785)	(2.293)	(3.716)
$\text{Disaster x Concurrent Event}_{t-3}$		-1.025	-0.257	-1.200
		(0.802)	(1.562)	(1.412)
$\text{Disaster x Concurrent Event}_{t-4}$		1.159	-1.306	1.933
		(1.931)	(2.375)	(2.664)
Month-by-Year FEs	X	X	X	X
ETF FEs	X	X	X	X
Observations	14,430	14,430	4,826	9,604
Adjusted R^2	0.026	0.026	-0.004	0.040

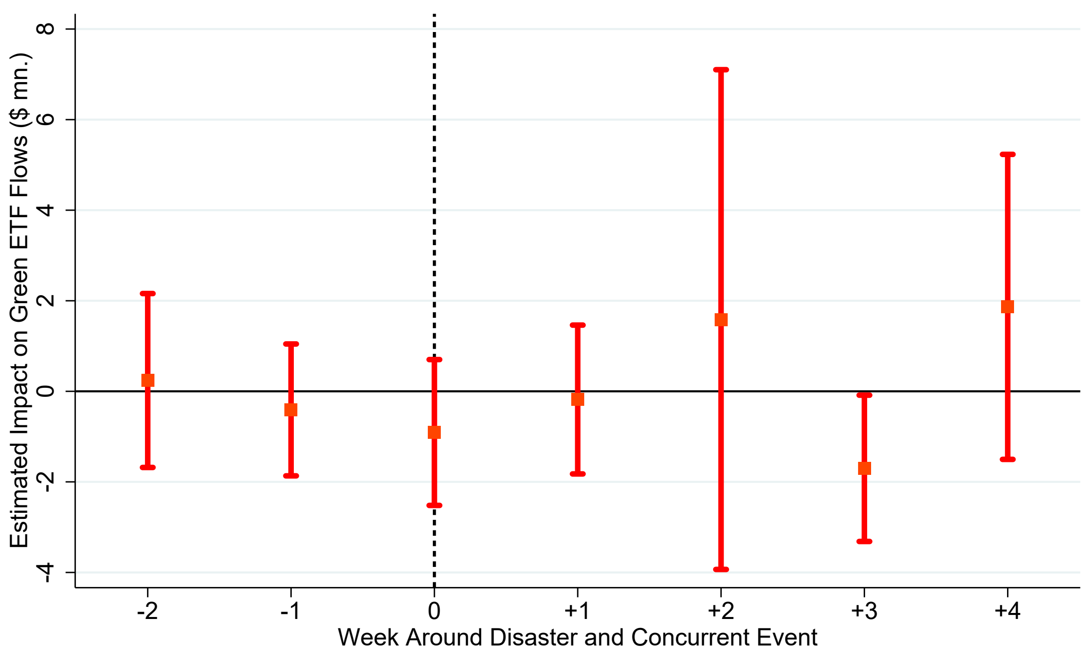
Notes: OLS regressions with robust standard errors two-way clustered by ETF and by month-year shown in parentheses. The unit of observation is ETF-week. The dependent variable measures the volume of investment flows into green-labeled ETFs (in $mn.). Explanatory variables indicate the presence of U.S. natural disasters or concurrent events (U.S. terror incidents, mass shootings, or technological accidents) within a given week. Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Figure 4: Event Study Results – Disasters, Concurrent Events, and Green ETF Flows, 2015-2020

(a) Without Concurrent Event



(b) With Concurrent Event (Terror, Mass Shooting, or Accident)



Notes: Panel (a) illustrates the changes in investment flows into green-labeled ETFs in the wake U.S. natural disasters, without the occurrence of concurrent distracting events. Panel (b) presents the corresponding effects observed when concurrent events (terror attacks, mass shootings, or technological accidents) occur simultaneously. The related estimation results can be found in column (4) of Table 3. Both panels include 90% confidence intervals.

In summary, the documented effects of increasing flows into green ETFs following climate disasters align with results found on investor attention to eco-friendly investments using Google searches. Combining these two sets of evidence, retail investors seem to increase their interest and actual investments in green ETFs, reflecting an increase in green sentiment following natural disasters (not driven by changes in ETFs' fundamental value). The evidence suggests that media plays a pivotal role as a disseminator of exogenous stimuli affecting investment behavior. When distracting events occur and draw attention away from disasters, we observe no changes in investor interest or actual green investments.

To further explore this plausible mechanism, the next section investigates the interplay between disaster occurrences, concurrent events, and media reporting on climate change.

6 Media Climate Coverage and Brown ETF Flows

In this section, we perform complementary analyses on media climate change coverage and investments in brown ETFs in the wake of disasters and concurrent attention-grabbing events. Following a description of the coding of dependent variables, we present the event study results using the same econometric specifications as in the previous analyses.

6.1 Media Climate Change Concerns

We examine whether and to what extent coverage of climate change concerns in news media changes around U.S. natural disaster events, and importantly, whether this is moderated by the occurrence of concurrent attention-grabbing events. For this purpose, we rely on the Media Climate Concern Index developed by Ardia et al. (2022).[17] This index aims to capture both the extent of media coverage and expressed concerns about climate change. It draws from climate change reporting across eight major U.S. newspapers, including The New York Times, The Wall Street Journal, and The Washington Post.[18]

The index is assessed through a two-step process. Initially, an article-level concern score is calculated by analyzing the extent to which the article discusses future risk events and the perceived increase in climate-related risks. Subsequently, these article-level scores are aggregated daily by multiplying the number of climate change-related articles by the average concern score of those articles on a particular day across all sources. Thus, this method captures both the intensity of climate change coverage and the average level of concern expressed in those articles on a specific day. The authors show that the index effectively reflects several significant climate change events that are likely to increase public attention and concern about climate change.

Table 4 presents the related estimates where we regress the Media Climate Concern Index (weekly average) on disaster and concurrent event leads and lags, along with their respective

[17] The index can be accessed via www.sentometrics-research.com.

[18] The version of the index used corresponds to the 2020 version as outlined in the National Bank of Belgium Working Paper.

interactions. The econometric specification used is virtually the same as the one used in the analysis of Google search data – see model equation (1). In column (1), we include only disaster leads and lags, while column (2) incorporates concurrent events and their interactions with disasters. Columns (3) and (4) divide the sample into older (2003-2010) and newer (2011-2018) periods, respectively. Before running the regressions, we standardized the Media Climate Concern Index by dividing it by its standard deviation. Therefore, the coefficients indicate changes in terms of standard deviations, facilitating the interpretation of effect sizes.

Generally, over the full sample period from 2003 to 2018, the results show no significant changes in climate change concern coverage either in the wake of disasters or when distracting events occur concurrently. However, when restricting the analysis to the more recent period from 2011 to 2018 – which includes the post-2015 period when the Paris Agreement was passed and general climate awareness increased – we document significant increases in climate concern coverage in the first three weeks following a disaster, amounting to 0.20 to 0.26 standard deviations in magnitude. The corresponding event study estimates are graphically visualized in Figure 5. Consistent with the explanation that distracting events crowd out coverage of disasters and expressed climate concerns, we find no significant changes in climate coverage when attention-grabbing events occur concurrently during disaster weeks. None of the estimated changes in climate coverage around disasters, given that concurrent events also happen, are significantly different from zero.

Interestingly, for the older sample period from 2003 to 2010, we document significantly less climate change concern coverage in the three weeks following disasters, with reductions ranging from 0.22 to 0.38 standard deviations in the index. However, when simultaneous distracting events occur alongside disasters, this diminished climate concern coverage is not observed (none of the corresponding t-tests on the significance of situations when both disasters and concurrent events happen allow us to reject the null hypothesis of no effects). These findings suggest that in the older period, when general climate awareness was not as pronounced, media coverage may have focused mainly on the catastrophes themselves rather than on related climate concerns, even leading to a crowding out of the latter. Conversely, when both disasters and other attention-grabbing events occurred simultaneously in this older period, the focus of media outlets may have been distributed among all events, with none receiving particularly heightened attention. This effectively resulted in no significant crowding out of climate concern coverage.

Taking the evidence on media coverage of climate change concerns together with the prior results on investor behavioral changes, the findings suggest that for the newer period covering the post-2015 Paris Agreement era, media coverage of climate change concerns is indeed responsible for the documented increases in green sentiment in the wake of disasters, driving investors to allocate more funds to green assets. In other words, if the media does not intensively cover climate change concerns following disaster events – because something else happens by chance that also attracts media and thus investor attention – green sentiment among investors does not change. This underscores the importance of media reporting on climate change challenges in prompting investors to adopt more sustainable investing strategies.

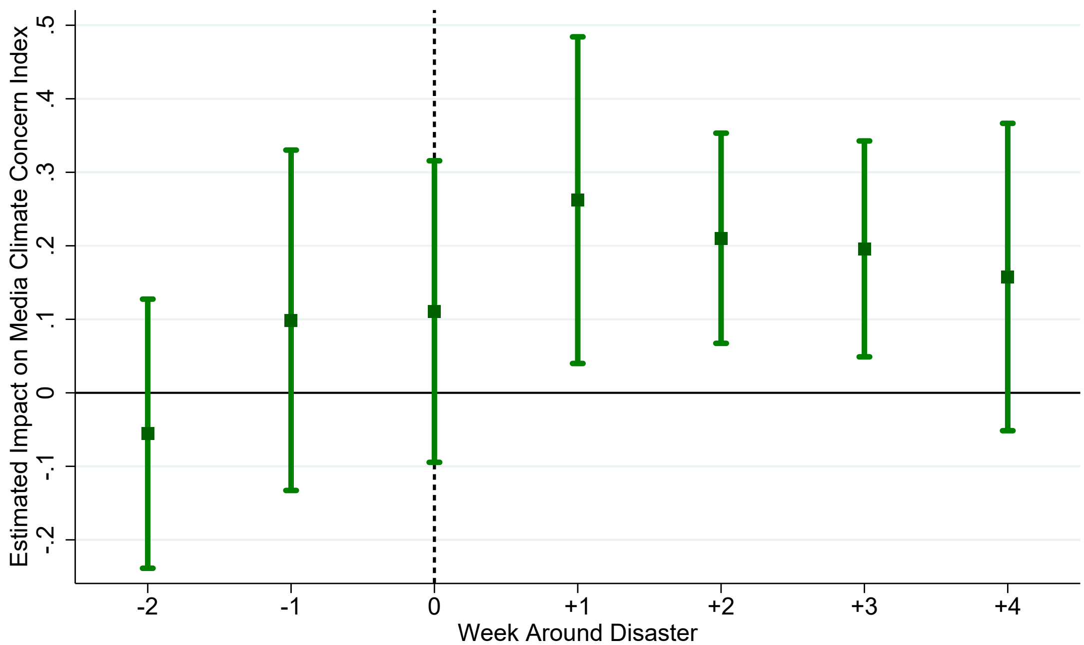
Table 4: Disasters, Concurrent Events, and Media Climate Concerns, 2003-2018

Dependent Variable: *Media Climate Concern Index*	(1) disasters only	(2) +distraction	(3) 2003-2010	(4) 2011-2018
Disaster$_{t+2}$	0.002	0.016	0.102	-0.056
	(0.080)	(0.091)	(0.148)	(0.111)
Disaster$_{t+1}$	0.137	0.092	0.168	0.099
	(0.086)	(0.089)	(0.117)	(0.141)
Disaster$_{t}$	0.056	0.052	0.062	0.111
	(0.093)	(0.094)	(0.126)	(0.125)
Disaster$_{t-1}$	-0.065	-0.064	-0.324*	0.262*
	(0.118)	(0.133)	(0.181)	(0.135)
Disaster$_{t-2}$	-0.078	-0.130	-0.380**	0.210**
	(0.083)	(0.108)	(0.150)	(0.087)
Disaster$_{t-3}$	-0.000	-0.054	-0.225*	0.196**
	(0.085)	(0.094)	(0.127)	(0.089)
Disaster$_{t-4}$	0.034	-0.044	-0.178	0.158
	(0.083)	(0.083)	(0.106)	(0.127)
Concurrent Event$_{t+2}$		0.015	-0.033	0.008
		(0.083)	(0.081)	(0.145)
Concurrent Event$_{t+1}$		-0.001	-0.108	0.040
		(0.092)	(0.106)	(0.153)
Concurrent Event$_{t}$		0.083	-0.083	0.200
		(0.105)	(0.130)	(0.159)
Concurrent Event$_{t-1}$		0.254**	0.089	0.340*
		(0.120)	(0.132)	(0.181)
Concurrent Event$_{t-2}$		0.076	-0.092	0.192
		(0.152)	(0.131)	(0.232)
Concurrent Event$_{t-3}$		0.079	0.038	0.106
		(0.126)	(0.131)	(0.186)
Concurrent Event$_{t-4}$		0.060	0.016	0.089
		(0.108)	(0.118)	(0.166)
Disaster x Concurrent Event$_{t+2}$		-0.133	-0.264	0.048
		(0.193)	(0.199)	(0.358)
Disaster x Concurrent Event$_{t+1}$		0.197	0.231	0.247
		(0.253)	(0.358)	(0.483)
Disaster x Concurrent Event$_{t}$		-0.151	0.324	-0.503
		(0.264)	(0.301)	(0.504)
Disaster x Concurrent Event$_{t-1}$		-0.149	0.506***	-0.589
		(0.219)	(0.178)	(0.459)
Disaster x Concurrent Event$_{t-2}$		0.185	0.907*	-0.405
		(0.294)	(0.453)	(0.397)
Disaster x Concurrent Event$_{t-3}$		0.178	0.516	-0.089
		(0.243)	(0.358)	(0.289)
Disaster x Concurrent Event$_{t-4}$		0.410*	0.707**	0.124
		(0.214)	(0.307)	(0.289)
Month-by-Year FEs	X	X	X	X
Observations	807	807	417	390
Adjusted R^2	0.569	0.572	0.573	0.453

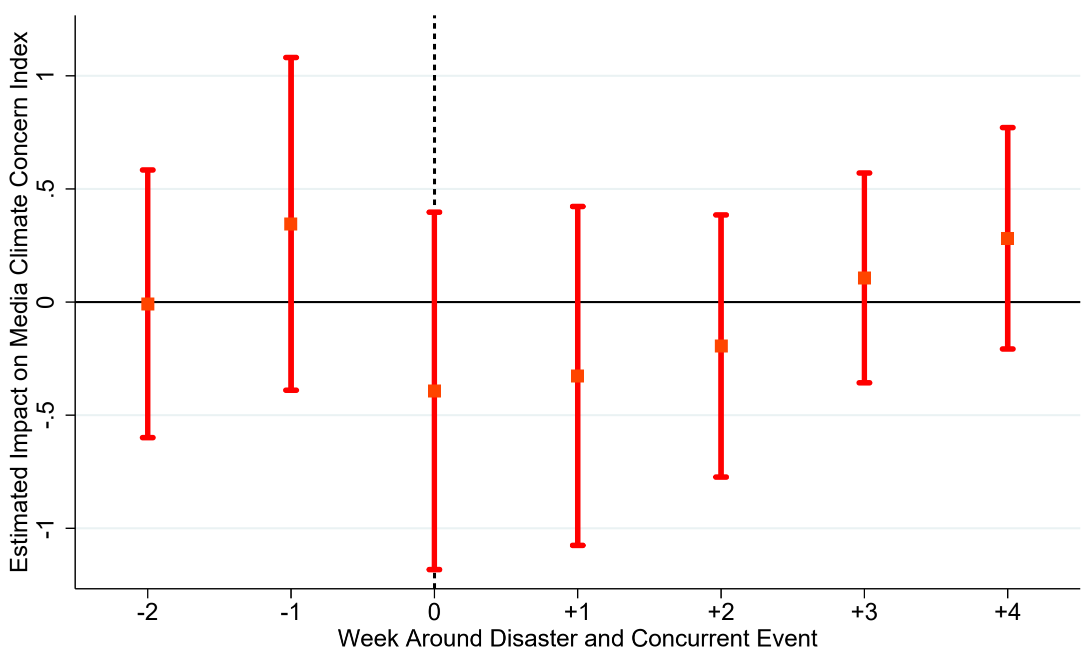
Notes: OLS regressions with robust standard errors clustered by quarter shown in parentheses. The unit of observation is a particular week. The dependent variable is the overall Media Climate Concern Index (Ardia et al., 2022), adjusted by dividing it by its standard deviation. The original index has a mean value of 0.445 and a standard deviation of 0.265. Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Figure 5: Event Study Results – Disasters, Concurrent Events, and Media Climate Concerns, 2011-2018

(a) Without Concurrent Event



(b) With Concurrent Event (Terror, Mass Shooting, or Accident)



Notes: Panel (a) illustrates the changes in expressed climate concerns across U.S. newspapers in the wake of disasters without the occurrence of concurrent distracting events. Panel (b) presents the corresponding effects observed when concurrent events (terror attacks, mass shootings, or technological accidents) occur simultaneously. For measuring climate change concerns in the news media, we use the Media Climate Concern Index constructed by Ardia et al. (2022). The related estimation results can be found in column (4) of Table 4. The effects are expressed in standard deviations. Both panels include 90% confidence intervals.

6.2 Brown ETF Flows

One might expect that the increasing green sentiment in the wake of disasters, driven by heightened media focus on disasters and climate change concerns, could be accompanied by corresponding disinvestments out of brown ETFs. On the one hand, retail investors might sell their holdings in brown ETFs to fund investments in green ETFs. On the other hand, investors might liquidate their brown ETFs without reallocating to green ETFs due to increasing climate awareness following disasters, similar to the reasons why some investors might shift towards green investments.

Table 5 presents the regression results for model equation (2), using brown ETF flows as the dependent variable. The keywords used to label brown ETFs are 'oil', 'petroleum', 'gas', 'coal', and 'mining'. Column (1) shows the estimation results for the full sample period (2005-2020), focusing solely on disaster leads and lags. Column (2) incorporates the concurrent event variables along with their interaction terms with disasters. In column (3), we analyze the subsample period from 2005-2014, while column (4) focuses on the newer period from 2015-2020 (post-Paris Agreement).

The results indicate that there is no significant change in brown ETF flows during the weeks before and after a disaster, or during the week of the disaster itself, for the first three specifications that focus on the full period 2005-2020 and the pre-Paris Agreement period until 2014. However, in specification (4), focusing on the subsample from 2015-2020 (post-Paris Agreement), we observe pronounced reductions in brown ETF flows following disasters. The evolution of these effects is depicted in Figure 6. Specifically, we observe decreases in brown ETF flows amounting to approximately \$10.1 million (not significant) and \$5.5 million in the two weeks preceding a disaster, relative to the reference period. During the disaster week itself, brown ETF flows decrease by an average of \$7.7 million. This negative trend continues into the week following the disaster, with a decrease of \$3.6 million (not significant). Furthermore, we document even larger declines two and three weeks after disasters, although these effects are not estimated precisely. Given that the mean flows for brown ETFs amount to \$1.1 million during the 2015-2020 period, these disinvestments around disasters represent a substantial decrease.

Consistent with investors being distracted from disasters and climate change concerns when other attention-grabbing events occur simultaneously, we do not observe significant changes in brown ETF flows – as shown in panel (b) of Figure 6.

In summary, the findings on disinvestments from brown ETFs following disasters in the post-Paris Agreement period, and their moderation by concurrent attention-grabbing events, are consistent with the evidence we document on corresponding increases in green ETF investments.

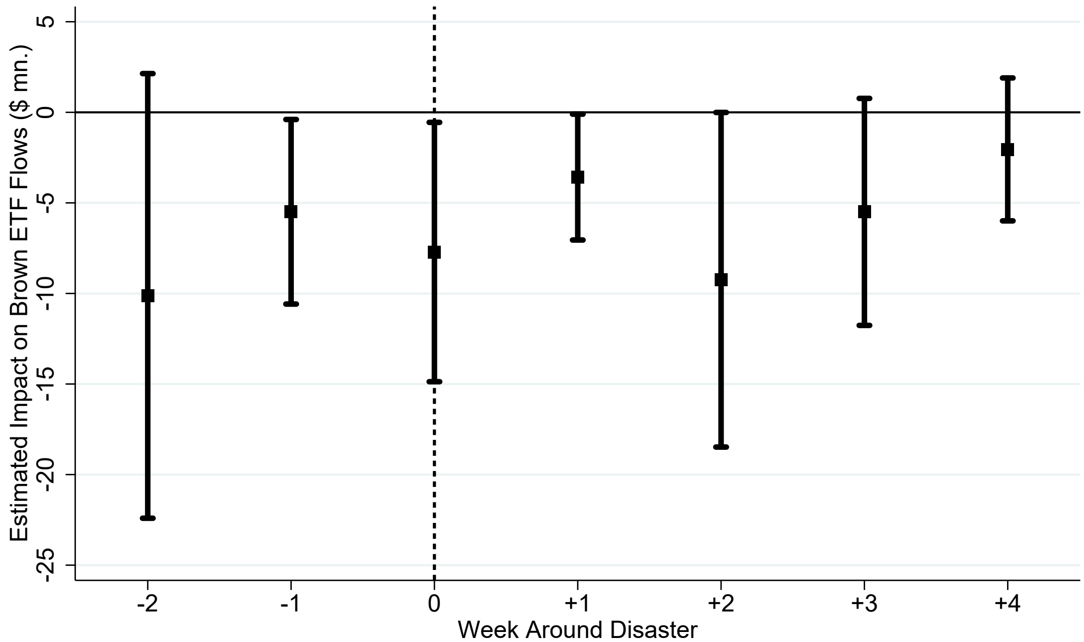
Table 5: Disasters, Concurrent Events, and Brown ETF Flows, 2005-2020

Dependent Variable: *Brown ETF Flows*	(1) disasters only	(2) +distraction	(3) 2005-2014	(4) 2015-2020
Disaster$_{t+2}$	-5.281	-6.346	-5.187	-10.14
	(4.612)	(6.363)	(7.106)	(7.462)
Disaster$_{t+1}$	0.065	0.349	4.389	-5.491*
	(1.527)	(2.131)	(2.975)	(3.097)
Disaster$_{t}$	-2.479	-0.518	2.511	-7.714*
	(2.375)	(1.896)	(1.632)	(4.352)
Disaster$_{t-1}$	-1.821	-2.250	-3.780	-3.576
	(1.537)	(2.371)	(4.553)	(2.112)
Disaster$_{t-2}$	-1.368	-0.956	4.393	-9.245
	(2.280)	(2.709)	(3.352)	(5.615)
Disaster$_{t-3}$	-2.086	-4.134	-3.674	-5.498
	(2.091)	(3.016)	(3.866)	(3.809)
Disaster$_{t-4}$	-1.519	-1.750	-2.759	-2.048
	(1.643)	(2.491)	(3.753)	(2.398)
Concurrent Event$_{t+2}$		-1.010	-2.531	-0.438
		(1.637)	(4.279)	(1.519)
Concurrent Event$_{t+1}$		-0.464	-1.228	0.454
		(1.423)	(2.846)	(1.935)
Concurrent Event$_{t}$		0.240	2.879	-0.795
		(1.526)	(4.463)	(1.521)
Concurrent Event$_{t-1}$		0.014	-0.093	1.466
		(1.129)	(2.971)	(1.627)
Concurrent Event$_{t-2}$		0.508	0.956	-0.102
		(0.872)	(2.524)	(1.029)
Concurrent Event$_{t-3}$		1.168	1.798	0.743
		(2.184)	(3.455)	(1.611)
Concurrent Event$_{t-4}$		3.123*	7.521*	1.978
		(1.617)	(3.526)	(2.008)
Disaster x Concurrent Event$_{t+2}$		6.332	5.158	11.45
		(8.920)	(9.627)	(12.01)
Disaster x Concurrent Event$_{t+1}$		1.504	-7.356	11.48
		(4.513)	(7.290)	(10.26)
Disaster x Concurrent Event$_{t}$		-10.07*	-14.84	-2.898
		(5.244)	(9.620)	(5.496)
Disaster x Concurrent Event$_{t-1}$		1.287	-3.434	9.862
		(3.921)	(6.575)	(6.822)
Disaster x Concurrent Event$_{t-2}$		-1.847	-11.039	12.35
		(5.426)	(12.24)	(7.347)
Disaster x Concurrent Event$_{t-3}$		7.802	7.893	9.398
		(5.823)	(7.815)	(8.096)
Disaster x Concurrent Event$_{t-4}$		0.958	-5.681	3.434
		(4.447)	(5.957)	(6.543)
Month-by-Year FEs	X	X	X	X
ETF FEs	X	X	X	X
Observations	9,560	9,560	4,421	5,139
Adjusted R^2	-0.007	-0.006	-0.010	-0.000

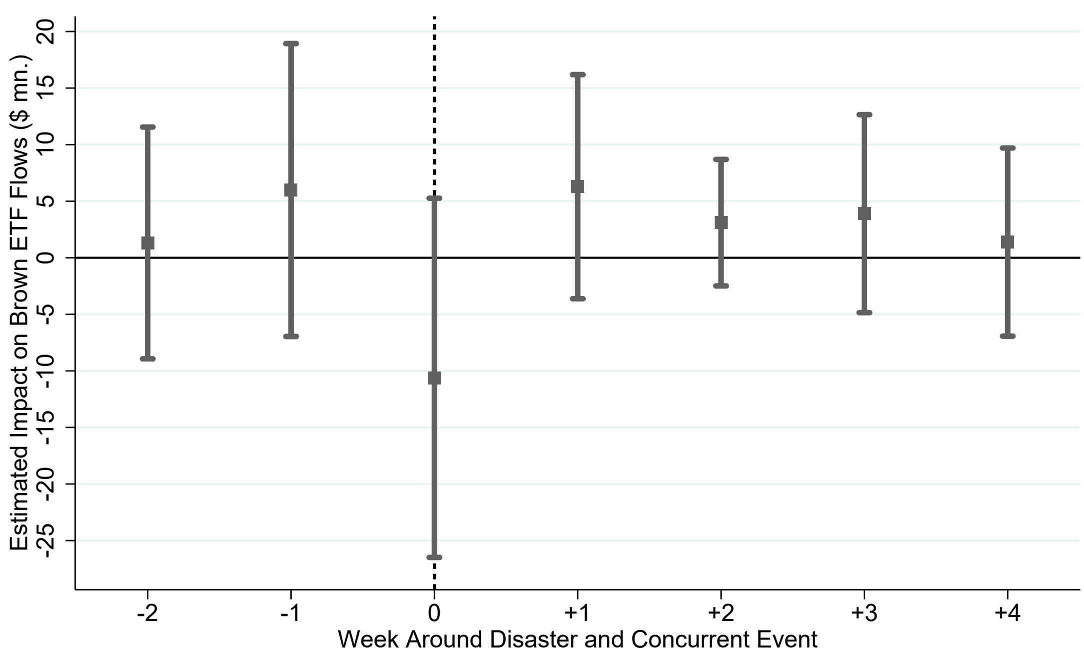
Notes: OLS regressions with robust standard errors two-way clustered by ETF and by quarter shown in parentheses. The unit of observation is ETF-week. The dependent variable measures the volume of investment flows into brown-labeled ETFs (in $mn.). Explanatory variables indicate the presence of U.S. natural disasters or concurrent events (U.S. terror incidents, mass shootings, or technological accidents) within a given week. The mean value and standard deviation for brown ETF flows are 0.953 and 45.63 for the full sample (1.117 and 45.16 for the 2015-2020 period). Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Figure 6: Event Study Results – Disasters, Concurrent Events, and Brown ETF Flows, 2015-2020

(a) Without Concurrent Event



(b) With Concurrent Event (Terror, Mass Shooting, or Accident)



Notes: Panel (a) illustrates the changes in investment flows into brown-labeled ETFs in the wake U.S. natural disasters, without the occurrence of concurrent distracting events. Panel (b) presents the corresponding effects observed when concurrent events (terror attacks, mass shootings, or technological accidents) occur simultaneously. The related estimation results can be found in column (4) of Table 5. Both panels include 90% confidence intervals.

7 Robustness

To ensure the robustness of our main findings on increasing interest in eco-friendly investments, actual increasing flows into green ETFs, as well as increased media climate concern coverage after disasters, we perform a series of estimations where we vary the estimated specifications and data selection criteria.

Google Searches Eco-Investing In Table 6, we present different specifications for the analysis on eco-friendly investing intentions using Google search data. The first column shows the baseline specification for the newer post-Paris Agreement period (2015-2019) – model (4) from Table 1. Specification (2) includes two additional lead week dummies to the model to further investigate the observation from the baseline model, which shows a significant increase in Google searches on eco-friendly investments two weeks before disasters actually occur. Adding more lead weeks does not confirm this finding. We observe no significant change in Google searches before disaster weeks with this extended lead specification. However, in the first and second weeks following a disaster, Google searches on 'eco-investing' rise significantly, confirming the robustness of our baseline estimates. In columns (3), (4), (5), and (6), we sequentially add the leads and lags, starting only with the disaster week dummy. The related estimates confirm the main finding that there is a particular uptick in Google searches related to eco-friendly investments in the week following disasters. Importantly, given the additional occurrences of distracting events, none of the specifications allow us to reject the hypothesis that there is no change in Google searches on the topic of eco-investing in the week following disaster activity (see p-values from the related t-tests).

Table 6: Robustness – Disasters, Concurrent Events, and Google Searches for Eco-Investing, 2015-2019

Dependent Variable: *Google Searches 'Eco-Investing'*	(1) baseline 2015-2019	(2) more leads	(3) less leads/ lags I	(4) less leads/ lags II	(5) less leads/ lags III	(6) less leads/ lags IV
Disaster_{t+4}		-3.335				
		(2.862)				
Disaster_{t+3}		-0.707				
		(3.332)				
Disaster_{t+2}	4.316**	1.911				
	(1.874)	(2.906)				
Disaster_{t+1}	4.116	1.938			0.191	1.825
	(2.664)	(3.041)			(1.411)	(2.033)
Disaster_{t}	6.896*	4.809	1.955	2.266	2.222	3.870
	(3.499)	(4.420)	(2.026)	(2.250)	(2.307)	(2.348)
Disaster_{t-1}	8.340***	6.639***		5.229**	5.332**	6.298**
	(2.683)	(2.210)		(2.206)	(2.043)	(2.277)
Disaster_{t-2}	5.624*	4.523**				4.222
	(2.941)	(2.013)				(2.737)
Disaster_{t-3}	1.067	0.352				
	(2.144)	(2.444)				
Disaster_{t-4}	-1.578	-1.467				
	(1.719)	(2.157)				
Concurrent Event_{t+4}		1.153				
		(1.756)				
Concurrent Event_{t+3}		4.273				
		(2.674)				
Concurrent Event_{t+2}	1.909	3.784*				
	(1.224)	(2.173)				
Concurrent Event_{t+1}	-0.272	1.825			-0.876	-0.716
	(2.001)	(2.243)			(1.508)	(1.718)
Concurrent Event_{t}	0.632	2.565	0.103	0.426	0.189	0.408
	(2.162)	(2.377)	(1.478)	(1.489)	(1.799)	(1.895)
Concurrent Event_{t-1}	2.755	3.783		2.292	2.131	2.174
	(2.541)	(2.700)		(1.415)	(1.506)	(1.816)
Concurrent Event_{t-2}	1.724	2.365				1.381
	(2.207)	(2.313)				(1.583)
Concurrent Event_{t-3}	-0.035	0.516				
	(2.298)	(2.208)				
Concurrent Event_{t-4}	-1.029	-0.496				
	(1.825)	(1.753)				
Disaster x Concurrent Event_{t+4}		-3.251				
		(3.727)				
Disaster x Concurrent Event_{t+3}		-6.389				
		(5.203)				
Disaster x Concurrent Event_{t+2}	-6.428**	-8.142				
	(3.052)	(5.324)				
Disaster x Concurrent Event_{t+1}	-4.474	-5.567			2.653	0.628
	(5.338)	(6.400)			(2.865)	(3.611)
Disaster x Concurrent Event_{t}	-7.307	-8.171	-0.401	-1.028	-0.298	-2.742
	(5.448)	(6.746)	(2.292)	(2.421)	(2.929)	(3.339)
Disaster x Concurrent Event_{t-1}	-12.70***	-10.57**		-5.986**	-5.830**	-7.987**
	(4.257)	(4.642)		(2.283)	(2.119)	(2.929)
Disaster x Concurrent Event_{t-2}	-9.185*	-6.403				-6.232*
	(4.507)	(4.268)				(3.197)
Disaster x Concurrent Event_{t-3}	-2.457	-1.750				
	(3.842)	(4.003)				
Disaster x Concurrent Event_{t-4}	1.296	0.637				
	(2.866)	(3.134)				
Month-by-Year FEs	X	X	X	X	X	X
Observations	260	260	260	260	260	260
Adjusted R^2	0.155	0.167	0.164	0.183	0.173	0.177
T-Test: Disaster_{t-1} + Disaster x Conc. $\text{Event}_{t-1} = 0$	0.096	0.308		0.473	0.668	0.285

Notes: OLS regressions with robust standard errors clustered by quarter shown in parentheses. The unit of observation is a particular week. The dependent variable is the Google search index for the topic of 'eco-investing', with a mean value of 3.285 and a standard deviation of 9.941. Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Green ETF Flows We perform several robustness tests and subsequently modify our baseline model in various ways, such as incorporating ETF specific trends, adjusting the number of leads/lags, and using alternative definitions of 'green'. The results are presented in Tables 7 and 8, and are described in detail as follows. As the final row in each table, we present the corresponding p-values of t-tests, testing the null hypothesis that the change in green ETF flows in the week following both a disaster and concurrent distracting event equals zero.

Column (1) in Table 7 presents the baseline model for the post-Paris Agreement period 2015-2020, which corresponds to column (4) from Table 3. In column (2), additional ETF-specific trends are included to account for varying time trends experienced by different ETFs. Here, the main disaster effect one week after the event remains of the same magnitude and statistically significant. Similarly, the null effect when both a disaster and distracting event occur is still observed, with the latter t-test revealing a p-value of 0.857. In columns (3), (4), (5), and (6), the number of leads and lags used is varied, opting for fewer leads/lags compared to the baseline specification. With these modifications, we aim to address the concern that monthly effects may partially absorb the effects of disaster leads and lags (i.e., when disaster leads and lags fully coincide within a specific month). The related results indicate an increase in green ETF flows one week after disasters similar to the one observed in the baseline specification, with the magnitude ranging from 4.13 to 4.67 $mn., though less precisely estimated.

In Table 8, column (1) again replicates the baseline model for the period 2015-2020 – model (4) in Table 3. Column (2) expands the analysis by including not only green equity ETFs (as in the baseline) but also green bond ETFs. In column (3), the scope is further extended to alternative ETFs (such as currency or sector-specific ETFs). The broader inclusion of other types of green-labeled ETFs results in a decrease in the estimated coefficient for changes in green ETF flows in the week following disasters from 4.26 to 3.47/3.39. However, significance of main disaster effect and the documented null effect with simultaneously occurring attention-grabbing events remain unaffected (with p-values of 0.937 and 0.953 for the latter tests). In column (4), the keywords used to classify green ETFs are varied. Instead of the keywords used in the baseline model, a reduced set of keywords is employed, following Berg et al. (2022a) (including 'SRI', 'social', 'ESG', 'green', 'sustain', 'environ', 'impact', 'responsible', 'clean', 'renewable'). The coefficient indicating changes in green ETF flows one week after disasters shows a slight increase, from 4.26 to 4.56, albeit losing statistical significance, likely due to the reduced sample size. In column (5), a second alternative set of keywords is used to classify green ETFs, restricting the selection to fewer terms, primarily focusing on highly specific sustainability-related words ('SRI', 'ESG', 'green', 'environ'). With this stricter keyword strategy, the coefficient estimating changes in green ETF flows one week after disasters becomes even more pronounced, increasing from $4.26 mn. to $7.67 mn. However, this comes at the expense of precision, again likely due to a reduced sample size as fewer ETFs meet this stringent criterion. Finally, in column (6), green ETFs are classified solely based on the keyword 'ESG'. Here we observe an again even higher increase in ETF flows one week after the disaster, which amounts to $9.01 mn. and is statistically significant at the 10% level. This effect is more than twice as high as the baseline model estimate. Again, in the presence of both disaster and distracting events, we cannot reject the null hypothesis that green ETF flows do not change significantly (p-value 0.413).

Alternative Reference Period for Event Study Analyses Finally, we conduct a different set of estimations by using an alternative reference period in the event study analyses on investor interest, actual investments, and climate concern coverage. Specifically, instead of using the baseline reference period that includes all weeks more than two weeks before and more than four weeks after a particular disaster week, we choose the two weeks immediately preceding disaster weeks as the reference period. Additionally, we include a lead for three weeks before disasters and define a binned lead endpoint that encompasses all weeks lying four weeks or more before a disaster week. Similarly, we employ binned endpoints for all weeks lying five or more weeks after weeks with disaster activity.

The related results for these alternative specifications are presented in Table 9, columns (1), (2), and (3), respectively, for the analyses on Google searches for 'eco-investing', actual investments into green ETFs, and expressed climate concerns across U.S. media. Figure 7 illustrates the results in event study graphs: panel (a) shows the effects when only disasters occur, and panel (b) shows the effects when concurrent attention-grabbing events occur in addition to disasters. In summary, we draw no different conclusions regarding the impacts of disasters and concurrent distracting events compared to our baseline findings.

We find robust evidence that both Google searches for eco-friendly investments and actual investments in green ETFs significantly and substantially increase in the week following serious disaster activity. Specifically, these effects amount to an increase of 6.18 in the Google search index (62% of a standard deviation) and a rise of $3.83 million in flows into green ETFs (approximately 14% of a standard deviation) compared to the reference period two weeks prior to the disaster week. Furthermore, expressions of climate change concerns in U.S. media increase by 0.19 to 0.28 standard deviations in the four weeks following a disaster week. Importantly, all these documented changes in Google searches for green investments, actual green investments, and media climate coverage are no longer observed when concurrent attention-grabbing events coincide with disasters.

Table 7: Robustness – Disasters, Concurrent Events, and Green ETF Flows, 2015-2020

Dependent Variable: *Green ETF Flows*	(1) baseline 2015-2020	(2) +ETF trends	(3) less leads/ lags I	(4) less leads/ lags II	(5) less leads/ lags III	(6) less leads/ lags IV
Disaster$_{t+2}$	-0.133	-0.156				
	(0.559)	(0.561)				
Disaster$_{t+1}$	1.245	1.225			1.202	0.880
	(1.135)	(1.142)			(0.730)	(1.064)
Disaster$_{t}$	-0.126	-0.152	-0.660	-0.261	-0.023	-0.068
	(1.451)	(1.461)	(0.966)	(0.756)	(0.762)	(0.931)
Disaster$_{t-1}$	4.263*	4.289*		4.128	4.670	4.540
	(2.498)	(2.513)		(3.056)	(3.169)	(3.384)
Disaster$_{t-2}$	-0.329	-0.299				-0.442
	(1.698)	(1.687)				(1.017)
Disaster$_{t-3}$	-0.501	-0.481				
	(1.420)	(1.424)				
Disaster$_{t-4}$	-0.068	-0.043				
	(1.806)	(1.806)				
Concurrent Event$_{t+2}$	-0.788	-0.775				
	(0.781)	(0.779)				
Concurrent Event$_{t+1}$	-0.776	-0.764			-0.069	-0.346
	(0.798)	(0.799)			(0.537)	(0.691)
Concurrent Event$_{t}$	-0.550	-0.508	0.141	-0.048	-0.205	-0.364
	(0.680)	(0.666)	(0.433)	(0.449)	(0.533)	(0.653)
Concurrent Event$_{t-1}$	-0.514	-0.464		0.234	0.184	-0.013
	(0.451)	(0.446)		(0.303)	(0.345)	(0.380)
Concurrent Event$_{t-2}$	-1.120	-1.123				-1.026
	(0.906)	(0.911)				(0.890)
Concurrent Event$_{t-3}$	0.761	0.767				
	(0.751)	(0.756)				
Disaster x Concurrent Event$_{t+2}$	0.372	0.412				
	(1.525)	(1.546)				
Disaster x Concurrent Event$_{t+1}$	-1.656	-1.620			-1.615	-0.816
	(1.755)	(1.772)			(1.229)	(1.738)
Disaster x Concurrent Event$_{t}$	-0.784	-0.755	0.437	-0.251	-0.876	-0.308
	(1.569)	(1.582)	(0.946)	(0.851)	(0.918)	(1.435)
Disaster x Concurrent Event$_{t-1}$	-4.444	-4.459		-4.676	-5.258	-4.590
	(2.670)	(2.680)		(3.028)	(3.205)	(3.416)
Disaster x Concurrent Event$_{t-2}$	1.914	1.913				2.423
	(3.716)	(3.723)				(3.793)
Disaster x Concurrent Event$_{t-3}$	-1.200	-1.207				
	(1.412)	(1.420)				
Disaster x Concurrent Event$_{t-4}$	1.933	1.898				
	(2.664)	(2.670)				
Month-by-Year FEs	X	X	X	X	X	X
ETF FEs	X	X	X	X	X	X
ETF Trends		X				
Observations	9,604	9,604	9,604	9,604	9,604	9,604
Adjusted R^2	0.040	0.071	0.039	0.041	0.040	0.040
T-Test: Disaster$_{t-1}$ + Disaster x Conc. Event$_{t-1}$ = 0	0.857	0.866		0.696	0.678	0.955

Notes: OLS regressions with robust standard errors two-way clustered by ETF and by month-year shown in parentheses. The unit of observation is ETF-week. The dependent variable measures the volume of investment flows into green-labeled ETFs (in $mn.). Explanatory variables indicate the presence of U.S. natural disasters or concurrent events (U.S. terror incidents, mass shootings, or technological accidents) within a given week. Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Table 8: Robustness – Disasters, Concurrent Events, and Green ETF Flows, 2015-2020

Dependent Variable: *Green ETF Flows*	(1) baseline 2015-2020	(2) +bond ETFs	(3) +altern. ETFs	(4) alt. green keywds. I	(5) alt. green keywds. II	(6) keyword 'ESG' only
Disaster_{t+2}	-0.133	-0.072	-0.078	-0.089	0.137	0.291
	(0.559)	(0.463)	(0.455)	(0.614)	(0.987)	(1.136)
Disaster_{t+1}	1.245	1.060	1.030	1.089	2.157	2.702
	(1.135)	(0.911)	(0.892)	(1.251)	(2.066)	(2.407)
Disaster_{t}	-0.126	-0.084	-0.086	-0.207	-0.082	0.007
	(1.451)	(1.167)	(1.149)	(1.575)	(2.486)	(2.832)
Disaster_{t-1}	4.263*	3.471*	3.392*	4.562	7.667	9.014*
	(2.498)	(2.046)	(2.000)	(2.809)	(4.580)	(5.328)
Disaster_{t-2}	-0.329	-0.311	-0.311	-0.318	-0.150	-0.052
	(1.698)	(1.395)	(1.370)	(1.834)	(2.941)	(3.333)
Disaster_{t-3}	-0.501	-0.379	-0.375	-0.436	-0.530	-0.540
	(1.420)	(1.133)	(1.112)	(1.518)	(2.289)	(2.565)
Disaster_{t-4}	-0.068	-0.046	-0.057	-0.170	0.052	0.136
	(1.806)	(1.486)	(1.458)	(1.939)	(2.986)	(3.309)
$\text{Concurrent Event}_{t+2}$	-0.788	-0.609	-0.598	-0.847	-1.158	-1.298
	(0.781)	(0.640)	(0.628)	(0.874)	(1.349)	(1.509)
$\text{Concurrent Event}_{t+1}$	-0.776	-0.616	-0.602	-0.966	-1.394	-1.609
	(0.798)	(0.647)	(0.634)	(0.895)	(1.331)	(1.490)
$\text{Concurrent Event}_{t}$	-0.550	-0.426	-0.417	-0.690	-1.254	-1.497
	(0.680)	(0.554)	(0.541)	(0.763)	(1.228)	(1.399)
$\text{Concurrent Event}_{t-1}$	-0.514	-0.365	-0.363	-0.646	-0.875	-0.950
	(0.451)	(0.354)	(0.346)	(0.484)	(0.699)	(0.781)
$\text{Concurrent Event}_{t-2}$	-1.120	-0.930	-0.915	-1.258	-1.913	-2.161
	(0.906)	(0.736)	(0.722)	(1.000)	(1.550)	(1.751)
$\text{Concurrent Event}_{t-3}$	0.761	0.652	0.639	0.829	1.226	1.403
	(0.751)	(0.633)	(0.619)	(0.836)	(1.251)	(1.399)
$\text{Concurrent Event}_{t-4}$	-1.095	-0.866	-0.849	-1.147	-1.716	-1.901
	(0.840)	(0.673)	(0.659)	(0.909)	(1.467)	(1.660)
Disaster x $\text{Concurrent Event}_{t+2}$	0.372	0.304	0.307	0.453	0.364	0.361
	(1.525)	(1.240)	(1.221)	(1.648)	(2.615)	(2.934)
Disaster x $\text{Concurrent Event}_{t+1}$	-1.656	-1.289	-1.247	-1.546	-3.571	-4.450
	(1.755)	(1.407)	(1.377)	(1.973)	(3.246)	(3.799)
Disaster x $\text{Concurrent Event}_{t}$	-0.784	-0.569	-0.540	-0.522	-1.564	-1.992
	(1.569)	(1.238)	(1.220)	(1.726)	(2.909)	(3.385)
Disaster x $\text{Concurrent Event}_{t-1}$	-4.444	-3.534	-3.439	-4.864	-8.948*	-10.59*
	(2.670)	(2.182)	(2.129)	(3.015)	(5.030)	(5.958)
Disaster x $\text{Concurrent Event}_{t-2}$	1.914	1.669	1.663	2.141	2.404	2.492
	(3.716)	(3.011)	(2.963)	(4.089)	(6.546)	(7.460)
Disaster x $\text{Concurrent Event}_{t-3}$	-1.200	-0.887	-0.865	-1.288	-2.734	-3.231
	(1.412)	(1.142)	(1.118)	(1.523)	(2.200)	(2.462)
Disaster x $\text{Concurrent Event}_{t-4}$	1.933	1.557	1.560	2.229	3.142	3.678
	(2.664)	(2.145)	(2.105)	(2.872)	(4.567)	(5.164)
Month-by-Year FEs	X	X	X	X	X	X
ETF FEs	X	X	X	X	X	X
Observations	9,604	11,853	12,105	8,611	5,499	4,857
Adjusted R^2	0.040	0.041	0.041	0.039	0.036	0.035
T-Test: Disaster_{t-1} + Disaster x Conc. $\text{Event}_{t-1} = 0$	0.857	0.937	0.953	0.772	0.434	0.413

Notes: OLS regressions with robust standard errors two-way clustered by ETF and by month-year shown in parentheses. The unit of observation is ETF-week. The dependent variable measures the volume of investment flows into green-labeled ETFs (in \$mn.). Explanatory variables indicate the presence of U.S. natural disasters or concurrent events (U.S. terror incidents, mass shootings, or technological accidents) within a given week. Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

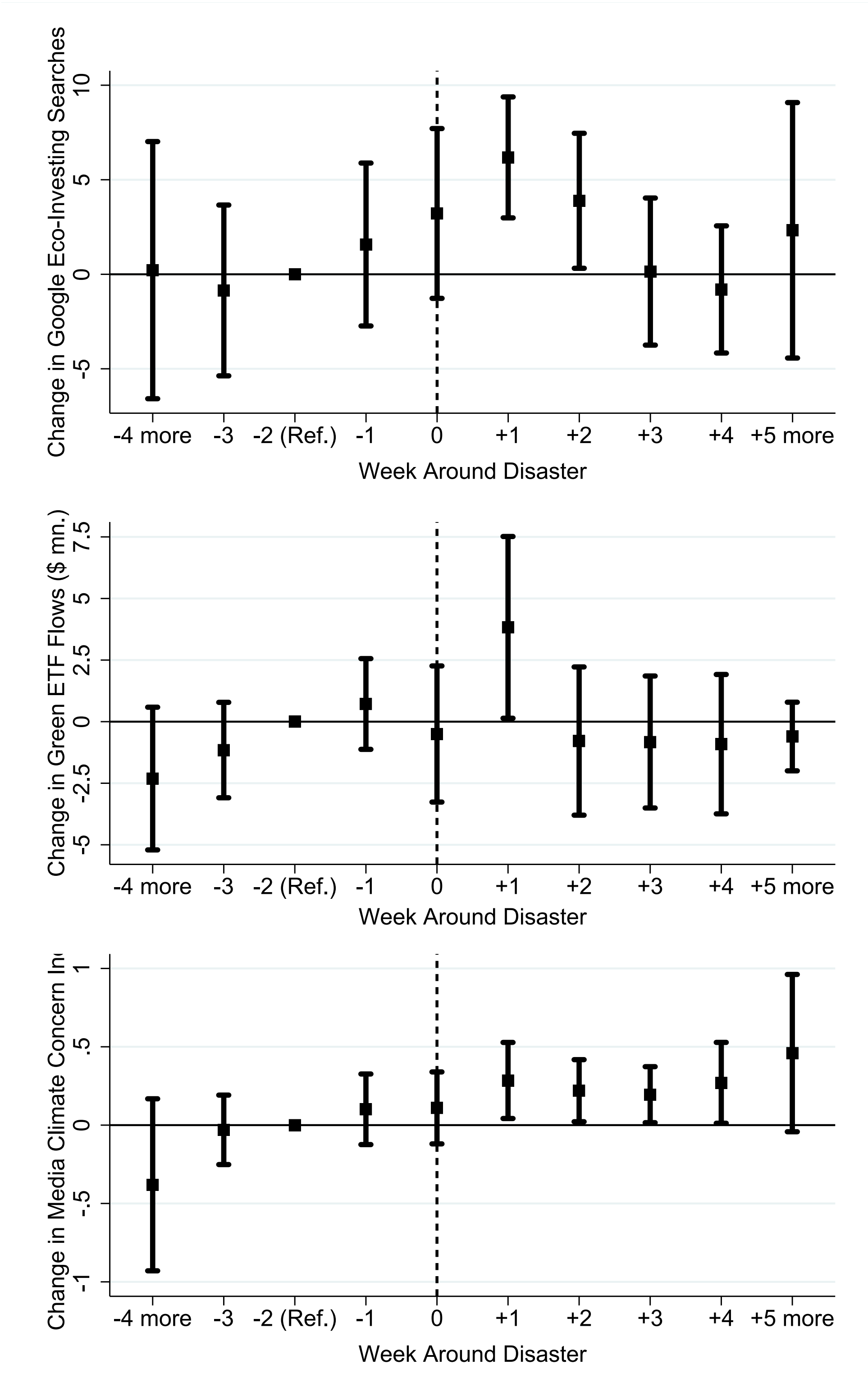
Table 9: Robustness – Alternative Reference Period for Event Study Analyses

Dependent Variable:	(1) Google Eco-Investing 2015-2019	(2) ETF Flows 2015-2020	(3) Media Climate Concerns 2011-2018
$\text{Disaster}_{t+4\text{ more}}$	0.218 (4.134)	-2.310 (1.761)	-0.381 (0.334)
Disaster_{t+3}	-0.854 (2.746)	-1.154 (1.177)	-0.030 (0.135)
Disaster_{t+1}	1.575 (2.619)	0.717 (1.120)	0.101 (0.137)
Disaster_{t}	3.218 (2.730)	-0.501 (1.680)	0.110 (0.140)
Disaster_{t-1}	6.183*** (1.945)	3.827* (2.242)	0.285* (0.148)
Disaster_{t-2}	3.887* (2.170)	-0.788 (1.829)	0.220* (0.120)
Disaster_{t-3}	0.143 (2.364)	-0.827 (1.628)	0.194* (0.109)
Disaster_{t-4}	-0.802 (2.044)	-0.914 (1.720)	0.270* (0.157)
$\text{Disaster}_{t-5\text{more}}$	2.326 (4.107)	-0.604 (0.846)	0.460 (0.305)
$\text{Concurrent Event}_{t+4\text{more}}$	-0.790 (2.342)	-0.289 (1.000)	-0.112 (0.219)
$\text{Concurrent Event}_{t+3}$	2.887 (2.107)	0.099 (0.750)	0.006 (0.104)
$\text{Concurrent Event}_{t+1}$	0.152 (1.720)	-0.418 (0.819)	0.057 (0.132)
$\text{Concurrent Event}_{t}$	1.069 (1.920)	-0.321 (0.726)	0.196 (0.145)
$\text{Concurrent Event}_{t-1}$	2.155 (2.415)	-0.305 (0.363)	0.358* (0.192)
$\text{Concurrent Event}_{t-2}$	1.312 (2.178)	-0.787 (0.741)	0.202 (0.255)
$\text{Concurrent Event}_{t-3}$	-0.125 (2.478)	0.782 (0.910)	0.102 (0.204)
$\text{Concurrent Event}_{t-4}$	-1.347 (1.995)	-1.207 (0.773)	0.096 (0.182)
$\text{Concurrent Event}_{t-5\text{more}}$	0.407 (4.151)	0.900 (0.836)	0.080 (0.289)
$\text{Disaster x Concurrent Event}_{t+4\text{more}}$	-3.083 (4.834)	2.854 (1.947)	0.065 (0.359)
$\text{Disaster x Concurrent Event}_{t+3}$	-2.147 (3.122)	1.536 (0.957)	-0.066 (0.256)
$\text{Disaster x Concurrent Event}_{t+1}$	-0.896 (4.729)	-1.608 (1.512)	0.203 (0.405)
$\text{Disaster x Concurrent Event}_{t}$	-3.051 (4.608)	-0.509 (1.264)	-0.500 (0.466)
$\text{Disaster x Concurrent Event}_{t-1}$	-7.648* (3.727)	-4.505 (2.888)	-0.633 (0.483)
$\text{Disaster x Concurrent Event}_{t-2}$	-5.532 (4.425)	1.879 (3.043)	-0.443 (0.483)
$\text{Disaster x Concurrent Event}_{t-3}$	-1.788 (3.437)	0.144 (2.048)	-0.392 (0.456)
$\text{Disaster x Concurrent Event}_{t-4}$	-5.802 (4.049)	0.568 (2.559)	-0.629 (0.417)
$\text{Disaster x Concurrent Event}_{t-5\text{more}}$	-5.148 (5.471)	-2.631 (2.469)	-0.733 (0.530)
Month-by-Year FEs	X	X	X
ETF FEs		X	
Observations	260	9,604	390
Adjusted R^2	0.142	0.040	0.450

Notes: OLS regressions with robust standard errors clustered by quarter (models 1 and 3), respectively two-way clustered by month-year and individual ETF (model 2), shown in parentheses. The unit of observation is week for models (1) and (3), and ETF-week for model (2). The dependent variables measure Google searches for the topic 'eco-investing' in model (1), the volume of flows into green-labeled ETFs (in $mn.) for model (2), and expressed media climate concerns for model (3) (Ardia et al., 2022; effects in standard deviations, with a mean value of 0.445 and a standard deviation of 0.265 for the original measure). Explanatory variables indicate the presence of U.S. natural disasters or concurrent events (U.S. terror incidents, mass shootings, or technological accidents) within a given week. Significance levels are denoted as follows: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Figure 7: Event Study Results Using Alternative Reference Period

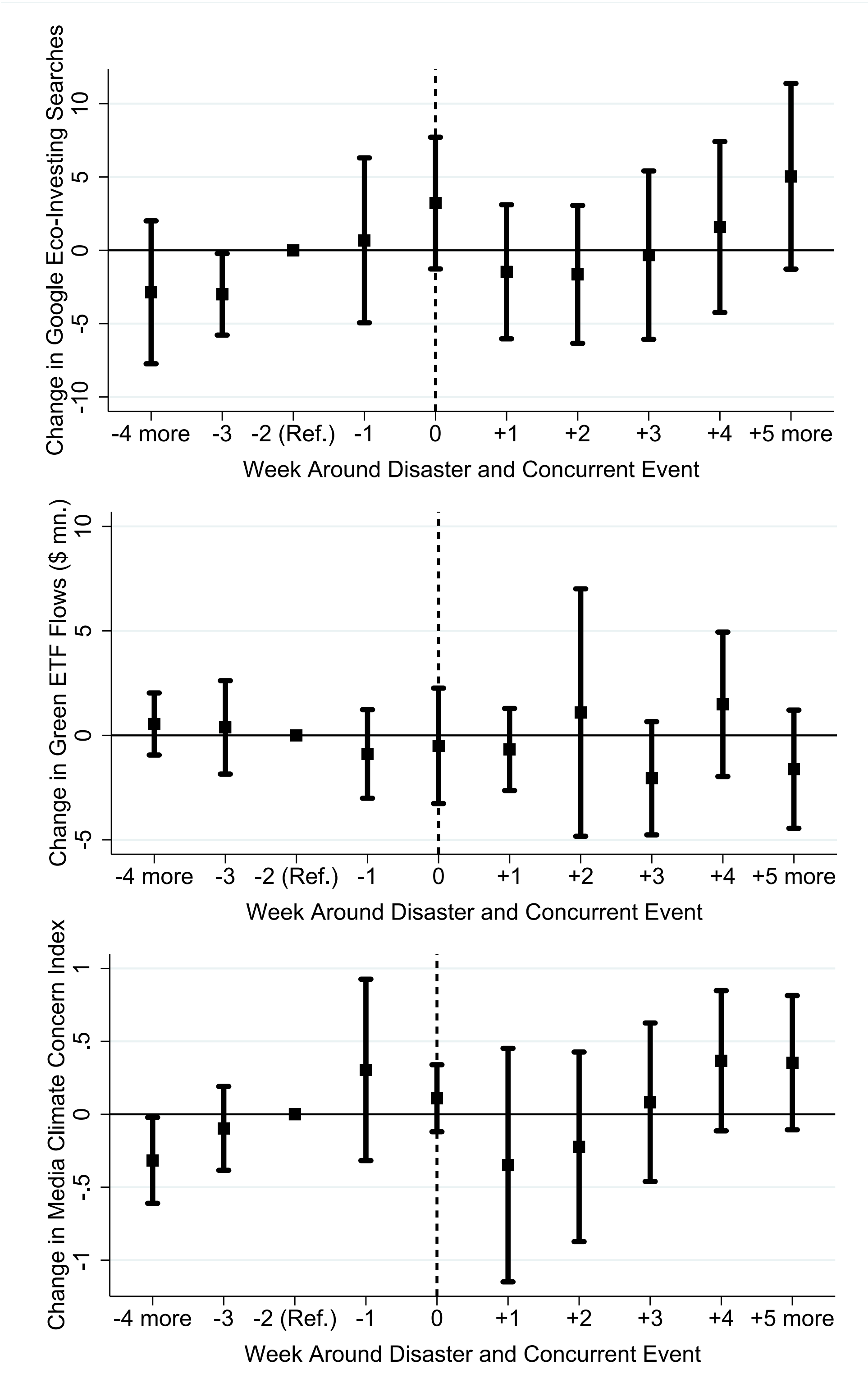
(a) Without Concurrent Event



Notes: Panel (a) illustrates the changes in (i) Google search queries for the topic 'eco-investing' (2015-2019), (ii) investment flows into green-labeled ETFs (2015-2020), and (iii) expressed climate concerns in newspapers (2011-2018, using the index constructed by Ardia et al., 2022; effects in standard deviations) in the wake of U.S. natural disasters, without the occurrence of concurrent distracting events. The related estimation results can be found in columns (1), (2), and (3) of Table 9. 90% confidence intervals included.

(Continued)

(b) With Concurrent Event (Terror, Mass Shooting, or Accident)



Notes: Panel (b) illustrates the changes in (i) Google search queries for the topic 'eco-investing' (2015-2019), (ii) investment flows into green-labeled ETFs (2015-2020), and (iii) expressed climate concerns in newspapers (2011-2018, using the index constructed by Ardia et al., 2022; effects in standard deviations) in the wake of U.S. natural disasters, when concurrent events (terror attacks, mass shootings, or technological accidents) occur simultaneously. The related estimation results can be found in columns (1), (2), and (3) of Table 9. 90% confidence intervals included.

8 Concluding Remarks

This paper investigates how natural disasters influence U.S. investor behavior towards green investments, specifically focusing on shifts in 'green sentiment' among retail investors. Hereby, we rely on observed flows into green-labeled ETFs in the primary market, reflecting changes in investors' non-fundamental demand, as suggested by Brown et al. (2021).

We document significant increases in both interest in eco-friendly investment strategies (proxied by Google searches) and actual investments in green ETFs in the wake of natural disasters. Importantly, these changing patterns are only observed in the post-2015 Paris Agreement period, characterized by generally higher levels of climate awareness. Specifically, following weeks with serious disaster activity in the U.S., we observe that Google searches for 'eco-investing' increase by over 80% of a standard deviation in the search index. Concurrently, flows into green ETFs are more than $4.2 million higher compared to non-disaster periods, where average flows are around $1 million.

However, our analysis also reveals a critical interaction effect: when disasters coincide with other major events such as terror attacks or mass shootings, the observed increase in green investing behavior (both interest and actual investments) is no longer observable. This suggests that investor attention, which is inherently limited, gets diverted away from climate concerns when competing attention-grabbing events occur simultaneously, thus crowding out potential shifts towards green investments. In subsequent analysis, utilizing the climate concern coverage index capturing expressed climate concerns across U.S. media (Ardia et al., 2022), we find evidence suggesting that media attention devoted to climate change concerns drives the documented shifts in investor behavior towards green investments.

The results of our study align with the notion that media attention to climate change concerns plays a key role in directing investor behavior towards sustainable investments. While we observe this to be true in the short term once disasters strike, this might also hold on a more general level where media acts as a disseminator of general climate change information and influences investor behavior accordingly.

The observed inflows into green ETFs following disasters indicate that the underlying shares of these ETFs have been purchased to create new ETF shares in the primary market, satisfying the excess demand in the secondary market. This heightened demand for the underlying shares can drive up the share prices of the issuing firms, making it more cost-effective for these companies to raise equity by selling their shares at the higher price. Whereas the observed disinvestment from brown ETFs in the wake of disasters creates adverse incentives for traditional energy sectors: the presence of green investors who consistently divest from brown firms can increase the long-term cost of capital for these companies by lowering their stock prices Cheng et al. (2024). This scenario provides financial incentives for these firms to adopt greener practices or transition towards more sustainable operations.

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