Are retail investors attracted to green firms? Evidence from extreme weather events

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Abstract

This paper investigates whether retail investors are more likely to invest in "green" companies after extreme weather events happened. Theoretical literature proposes that green stocks outperform brown stocks when concerns about climate change are unexpectedly strengthened. Retail investors, who are generally less sophisticated than institutional investors, are more likely to pay attention to prominent events, and may place greater importance on ESG information. Using extreme weather events as an exogenous shock to climate change concerns, this study finds that retail investors are more likely to net buy shares in green firms after an event. This study also finds that green firms have better cash flow prospects after extreme weather events. These findings suggest that extreme weather events make ESG-related risks more salient for retail investors and that firms with high ESG disclosure scores are better able to withstand such events.

Keywords: Retail investor; ESG investing; Extreme weather events; Salience
JEL Classification: G12, G32, G41, M14, Q54

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1. Introduction

Environmental, social, and governance (ESG) investing has grown rapidly over the last decade, sparking debates on investor preferences (Eccles et al., 2011; Edmans, 2022; Naveed et al., 2020; Moss et al., 2020). A theoretical study by Pastor et al. (2021) indicates that ESG factors capture unexpected changes in ESG concerns [1] (e.g., by either shifting customers' demand or investors' appreciation for green holding). However, little is known about whether and how the salience of unexpected ESG concerns shapes retail investors' trading decisions in green stocks.[2]

As a prominent type of ESG-related risk (Gisa, 2018), extreme weather events have accelerated to international agreements (e.g., the Paris Agreement) and new regulatory proposals (e.g., the Climate Action Plan) on ESG investing trends (Ardia et al., 2020). In their theoretical model, Pastor et al. (2021) argue that when concerns about climate change increase unexpectedly, investors are more willing to increase their ownership of green firms. In this paper, I empirically test the predictions related to investors' willingness to invest in green firms by using extreme weather events as an empirical setting to capture the increase in climate change concerns. The use of extreme weather events is particularly well suited because they can increase the salience of climate-related risks in investors' minds and act as a 'wake-up call' about climate risk.

Using extreme weather events as exogenous shocks, this study examines retail investors' trading activity in firms with high ESG disclosure scores as a proxy for revealed preferences for greenness. Given the increasing participation of retail investors in financial markets (20 % or more US stock volume (Eaton et al., 2021)), it is important to understand retail investors' trading activity. Meanwhile, retail investors actively reallocate capital in response to sentiment and preference shifts (Dottling and Kim, 2022), and are more attracted to attention-grabbing events than institutional investors (Klibanoff et al., 1998). As attention-grabbing events link to net buying activities by retail investors

[1] ESG concerns include but are not limited to climate change, human rights and animal rights.

[2] ESG profile ranges assets from green to brown (Avramov et al., 2022); ESG investors are regarded as green investors (Goldstein et al., 2022), and the terms greenness, green firms and stocks, and high-ESG disclosure will be used interchangeably.

(Seasholes and Wu, 2007), I posit that retail investors will net buy more green firms following extreme weather events.

The main sample consists of 29,394 firm-day retail trading activity observations between 2010 and 2020 in the United States. I measure retail trading activities using the retail order imbalance method developed by Boehmer et al. (2021), which indicates the number of daily buy and sell from retail investors for each firm. Extreme weather events are collected from Spatial Hazard Events and Losses Database (SHELDUS) (ASU Center for Emergency Management and Homeland Security, 2022) and are defined as events causing more than $ 1 billion in direct damage in less than 30 days at the county level, following Barrot and Sauvagnat (2016). I employ the difference-in-differences model specification. I define firms in the uppermost ESG disclosure score quintile from Bloomberg as green firms. Thus, the difference in investment in green firms before and after an extreme weather event captures whether retail investors will net buy more from green firms than from other firms after the event. In my main results, I find that retail investors buy more on green firms (high–ESG disclosure score firms) on days for which there is an extreme weather event after an extreme weather event, and the net buying activity mitigates 14 days after, along with the disappearance of extreme weather events.

I conduct several additional analyses. First, I test whether green firms have better cash flow after extreme weather events. The results show that green firms have a better cash flow along with a high ROA in the quarter after the extreme weather event, suggesting that green firms can better withstand climate-related risk. Second, I test whether retail investors net buy more on green firms that have a better cash flow after extreme weather events. The insignificant result indicates that retail investors' net buying activity toward green firms after extreme weather events is not related to fundamental performance. My third additional analysis is to add weather exposure[3] the annual report. Retail investors' selling activity of firms with high weather exposure is mitigated after extreme weather events if firms are regarded as green firms by retail investors. Fourth, I test a subsample of firms within an area affected by an extreme weather event.[4] The narrow scope could

[3] In addition to the third-party measurement of ESG-related information by using variety information, firms report their weather exposure in annual reports.

[4] Firms that are within 300 miles of an extreme weather event county is defined as affected firms, and it is a control

provide insights into whether retail investors focus specifically on green firms that are affected by extreme weather events. This result suggests that retail investors do not net buy more on green firms within the affected area after extreme weather events, suggesting that the increasing net buying activity is driven by firms outside the disaster area. Fifth, because firms with more social media presence may attract more retail investor attention, I control for high social media presence. The result is consistent with the main result.

There are several robustness tests. First, I examine an alternative definition of extreme weather events by calculating abnormally long durations.[5] There are 177 events with abnormally long durations over the last 10 years, with only two events overlapping with extreme weather events. Retail investors do not react significantly different to green firms after an event lasts abnormally long. This result suggests that retail investors react to extreme weather events that cause large direct damage rather than those that last longer. Second, I use trading volume as an alternative measure of order imbalance and show an increase in trading volume for green firms after an extreme weather event. Combined with the main results, I find that greater net buying activity drives increased trading volume. Third, I further explore whether the net buying activity of green firms originates from a particular dimension. I find that the results is statistically significant when firms within the uppermost quintile of high environmental disclosure scores, whereas insignificant for high social or governance scores. Therefore, retail investors pay attention to environmental dimension after extreme weather events. Fourth, to investigate whether retail investors react to all types of crises in the same manner, I use Covid-19 as another exogenous shock.[6] Comparing these two shocks can provide insight into how the nature of a shock influences retail investors' trading activity. The results indicate that retail investors sell more green firms during the Covid-19 pandemic from February 21, 2020, to April 25, 2020, consistent with the study by Dottling and Kim (2022). This result indicates an important differential reaction between retail investors and the different types

firm otherwise.

[5] An abnormally long duration is defined as a longer period compared with the average duration of this event over the past three years.

[6] Different with extreme weather events, Covid-19 is an economic crisis. During the lockdown period, some people lose their job. They are likely to be unable to consider the sustainability as normal and sell green firms. Meanwhile, they may in general sell more stocks because they need cash in hand.

of shocks. Finally, one may be concerned that other policies, such as positive macroeconomic news, may lead to more net buying activities. Therefore, I construct a placebo test using a randomized time variable in the difference-in-differences analysis to examine whether the result is still statistically significant. As only six estimates (representing 1.2% when repeating 500 times) have a t-value greater than the main regression results, this indicates that greater net buying activity does not occur in a randomized period. Therefore, the relationship between extreme weather events and changes in retail trading activities is not spurious.

This paper provides several important contributions. First, it contributes to the literature on the relationship between extreme weather events and retail investors' preference. Anderson and Robinson (2019) use Swedish data to show that, after experiencing a heat wave, investors shifted their retirement portfolios towards green investments, a behavior consistent with increased recycling and willingness to pay higher fees for eco-friendly funds. My study expands on this by suggesting that the influence of extreme weather events on green investments extends beyond just retirement portfolios to affect retail investors' overall investment strategies. My study extends studies by Choi et al. (2010) and Ghosh and Zhang (2021), both of which only examine local retail investors and their trading activity when facing abnormally high temperatures. By focusing on local retail investors, they argue that retail investors sell carbon-intensive firms at abnormally high temperatures. My study not only extends the examination of high temperatures to different types of extreme weather events but also examines all retail investors regardless of whether they are local to extreme weather events. Since net buying activity mitigates two weeks later, along with the disappearance of extreme weather events, this study contributes to the understanding of the dynamics of retail investor trading activity in response to extreme weather events and demonstrates that retail investors' increased net buying activity has a time-limited effect. My results, therefore, add to the argument that retail investors' order imbalances are less persistent during climate events (Finta, 2022).

Second, my study contributes to the understanding of whether investors trade on ESG information. The most related prior study is that of Moss et al. (2020), who find that retail investors do not trade significantly on more ESG press days than on non-event days. However, trading behavior in the application of Robinhood suggests more herding behavior, owing to information simplification and ease of trading (Barber et al., 2021). Therefore, the irrelevant relationship between trading activity and ESG information may be attributed to Robinhood's retail investor group. Relying on the special subpenny setup in the U.S. stock market to identify retail order imbalance following the calculation given by Boehmer et al. (2021), this study sheds new light on the changes in retail investors' trading activity in a large sample analysis (regardless of the platform retail investors use) of green and brown firms and examines extreme weather events as a shock that raises awareness of climate-related risks. Retail investors do not buy more on firms that have better performance after extreme weather events, which contributes to the understanding that retail investors trade on ESG information after extreme weather events due to the salient risk.

Third, I extend the existing studies to demonstrate that extreme weather events are important exogenous shocks to climate change awareness. Previous studies have examined other climate-related information, such as the climate-risk index (Huang et al., 2018; Mysiak et al., 2018) and climate news from newspapers (Engle et al., 2020; Li et al., 2023). For example, Li et al. (2023) indicate that retail investors react positively to firms' ESG news events, showing that ESG news is an important component of retail investors' portfolio allocation decisions. My study extends ESG news events related to firms themselves to the impact of unexpected changes in ESG concerns, that is, by using extreme weather events as the attention shock to individuals. Therefore, by focusing on the retail investor group, this study empirically tests the theoretical paper by Pastor et al. (2021), suggesting that extreme weather events are exogenous shocks and lead to unexpected changes in ESG concerns. The results suggest that extreme weather events could increase concerns about the salience of environmental issues, which shapes individual trading decisions regarding green stocks.

This paper is organized as follows. Section 2 reviews the literature on ESG investing, extreme weather events, and retail investors. Section 3 develops hypotheses based on the literature review. Section 4 describes the empirical design of the study. Section 5 reports the main results regarding retail investor trading activity after an extreme weather event, and presents additional analyses by examining the dimensions that drive the relationship between retail investor net buying in green firms after extreme weather events. Section 6 presents alternative measurements. Section 7 presents the results of several robustness tests. Finally, Section 8 concludes the study.

2. Literature Review

2.1. ESG Investing

The usefulness of ESG information has been widely discussed (Rose, 2020; Zumente and Bistrova, 2021; Yu and Van Luu, 2021; Gantchev et al., 2021; Moss et al., 2020). Environmental information refers to measurements of carbon emissions, waste pollution, natural resource conservation, and climate change risks. Social information indicates labor relations and product liability (e.g., supply chain management and community investment). Governance refers to corporate governance systems (e.g., board structure and auditing procedures). Increasingly, third-party ESG rating agencies cover companies, indicating that ESG scores are likely to be valuable to capital providers (Wong et al., 2021).

Martin and Moser (2016) find that investors positively value managers' decisions to contribute to environmental charities and respond positively to disclosure of such contributions. The experimental results show that retail investors are more willing to invest in companies that pursue ESG initiatives and disclose ESG. Cheng et al. (2021) use two experiments to document that, compared to professional investors, nonprofessional investors perceive ESG indicators as more important and are more willing to invest in the company if ESG indicators have greater strategic relevance. Latino et al. (2021) construct a quasi-natural experiment revealing that individual investors increase their participation in stocks with positive changes in their ESG rating and reduce their participation in firms recording negative changes in their ratings. These results are consistent with individual investors having increased their interest in sustainability and attending to changes in ESG ratings. In contrast, Moss et al. (2020) use the Robinhood database and find that the response of retail investors to ESG press releases does not differ from routine portfolio adjustments on non-event days. However, Barber et al. (2021) argue that the unique features of the Robinhood app, such as its provision of only five chart indicators, simplification of information and ease of trading, attract more inexperienced retail investors. Therefore, the examination of retail investors using only Robinhood data may be biased, and more evidence from a general sample[7] is needed.

ESG investing has also been examined under different types of exogenous shocks. Using Morningstar's carbon risk metric releases in April 2018 as an exogenous shock, Ceccarelli et al. (2021) find that fund managers significantly increase their demand on funds that are labelled as "low carbon." Hartzmark and Sussman (2019) use the release of Morningstar sustainability ratings as an exogenous shock and argue that higher-rated funds receive a large influx of funds, and lower-rated funds experience a large number of withdrawals after the release. They support their argument by using survey data, which indicate that naive investors feel that these companies will outperform in the future. They also identify faith as a loyal advocate of sustainable investment. This finding suggests that mutual fund investors' general demand for sustainability is not driven purely by agency issues. Lins et al. (2022) argues that Harvey Weinstein scandal and subsequent #METoo events make the non-sexist culture more salient, and investors changes their perference following the events. Therefore, their study proivde empirical evidence to support theoritcal paper by Pastor et al. (2021), suggesting that investors' responses to ESG issues can be driven by public information.

The importance and salience of climate risk have increased over time, and recent research indicates that an ESG lens can provide a heightened way to examine its effects on investment (Sautner and Starks, 2021). Climate risk is often divided into two categories: transitional and physical. Transition risks result from policy actions taken to transition the economy of fossil fuels, whereas physical risks result from climatic events, such as wildfires, storms, and floods (Erhemjamts et al., 2022).

2.2. Extreme Weather Events

The increasing number and magnitude of extreme weather events are some of the most notable consequences of climate change, having significant impacts on all parts of soci-

[7]The more generalizable calculation given by (Boehmer et al., 2021) the regulation given by NMS. Different with institutional orders, retail trades could get price improvement, frequently at a sub-penny level. TAQ data can be used to extract these trading relying on the special subpenny setup in the U.S. stock market. Based on the NMS regulation, these are recognized as retail investors trading.

ety (Sippel et al., 2015). Events such as hotter heat waves, drier droughts, and greater snowfall kill hundreds of people each year in the US and cause significant direct damage (Greenough et al., 2001). These events directly and immediately affect daily life, resulting in an increase awareness of climate change. More people now realise that even a 1.5 ºC increase in the average temperature by 2050 would pose a huge climate risk (Chomsky and Pollin, 2020; Kelkar and Bhadwal, 2007). Therefore, extreme weather events add to progress of international agreements (e.g., the Paris Agreement) and reactions from stakeholders and financial intermediaries. Previous studies examine some effects of extreme weather events on the financial market, firm performance and decision-making (e.g., Bourveau and Law, 2021; Dessaint et al., 2016).

Building on 38 expert interviews from various industry sectors in Germany, Bergmann et al. (2016) provide the first comprehensive investigation of how extreme weather events affect financial performance. They conclude that firms seriously impacted by extreme weather events cannot generate revenue growth. Empirically, Dessaint et al. (2016) find that when firms are in the neighbourhood of the disaster area, managers temporarily express more concerns about hurricane risk in 10-Ks/10-Q, consistent with salience theories of choice. Regarding hurricanes as disruptive life events, Bourveau and Law (2021) find that analysts who have just experienced a hurricane will become more risk-averse and pessimistic compared with analysts who have not, because analysts incorporate their risk perception into their scenario-based valuation models. Some argue that extreme weather events trigger fear in analysts, who will issue less-optimistic forecasting to non-affected firms, offsetting the optimism usually in their forecasts; hence, analysts will be more accurate after adverse events (Kong et al., 2021). Dehaan et al. (2017) find that analysts in locations with adverse weather exhibit slower information processing behaviours as measured by their level of activity in terms of forecasts, recommendations and target price updates. Furthermore, the impact of extreme weather events is not limited to the affected or neighbourhood areas. For example, natural disasters limit the credit supply of banks, even in areas that are not directly affected by the disaster (Furukawa et al., 2020). The reason is that the network effect influences reallocation from affected areas to unaffected areas. Similarly, Hu (2022) posits that social interaction is an important channel to obtain information, using flood insurance as an example. In detail, when far-away friends share flood experiences, one's attention may be drawn to flood risk, causing learning from the public information set about flood insurance or one's risk exposure. Such attention-triggered learning can be interpreted as the salience effect in the classical theoretical framework of salience.

After surveying global institutional investors regarding perceptions of climate risk, Krueger et al. (2020) find that although they rank it below financial, legal and operational risks, they still regard climate risk as important. Investors also believe that these risks already affect the firms in which they invest (Baldauf et al., 2020; Bolton and Kacperczyk, 2021), leading them to act [8] in their investments. In their theoretical model, Pastor et al. (2021) argue that when the climate-related risk becomes salient, as a type of ESG-related risk, investors are more willing to increase their ownership in green firms because brown firms have larger climate risk exposures. However, little is known about whether and how the salience of unexpected ESG concerns shape retail investors' trading decisions in green firms.

2.3. Retail Investor Trading Activity

Although retail investors may be less sophisticated than their institutional counterparts, they also face lower agency costs and liquidity constraints than institutional investors such as mutual funds (Chevalier and Ellison, 1999; Coval and Stafford, 2007). Therefore, retail investors have more flexibility in choosing stocks for investment. Also, several studies emphasise that retail investors impact the financial market due to their limited attention span. For example, Barber and Odean (2008) indicate that the attention of retail investors is particularly susceptible to attention-grabbing events. Compared with retail investors, attention is not a scarce source for institutional investors because they have more advanced technologies compared with retail investors to narrow their search to specific criteria.

[8] For example, Bolton and Kacperczyk (2021) indicate that investors ask for compensation if the firms they invest in are under high exposure to carbon emission risk.

Choi et al. (2020) use international evidence to indicate that retail investors sell carbon-intensive firms during hot months. Ghosh and Zhang (2021) use Indian market data to locate retail investors and compare the trading activities of green and brown firms. They suggest that an increase in investment flow towards green firms is related to extremely high temperatures. Both these studies examine retail investors' attention under their experiential learning, where people begin the learning process following their concrete experience. Nevertheless, under the salience theory, research discussing the relationship between extreme weather events and decision-making[9] provides an inspirational idea that retail investors may also change their trading activity even though they are not in the place where extreme weather occurs.

Based on salience theory, individual investors assign more importance to more prominent news and less importance to less prominent news, even though the two pieces of news may carry the same implication for economic fundamentals (Klibanoff et al., 1998). Consistent with this, current studies provide evidence of the economic shocks and the reactions from retail investors. Ozik et al. (2021) demonstrate that retail trading activity increases sharply during the Covid-19 lockdowns, especially among stocks receiving substantial Covid-19-related media coverage. Dottling and Kim (2022) regard Covid-19 as an ideal setting to examine the first major economic crisis. They conclude that retail flows in socially responsible investing (SRI) funds sharply declined, indicating that socially responsible investments are likely to be sensitive to income shocks resulting from Covid-19. Different with Covid-19 and financial crises, extreme weather events are environmental related, which serve to remind the public of the climate change risk (Ghosh and Zhang, 2021), impacting investor decision-making regarding equity change risk (Noy, 2017). However, how retail investors respond to this risk is uncertain.

[9] For example, the discussion about household flood insurance given by Hu (2022) or the credit supply of banks (Furukawa et al., 2020).

3. Hypothesis Development

Climate change is long-term because of human activity, emissions, energy use, and choices (Dale et al., 2011; Hadley et al., 2006; Johnson et al., 2009; Heidari and Pearce, 2016), making it difficult to observe directly. Extreme weather events, particularly unexpected ones, can be perceived either by direct experience or online media information (e.g., social media, Google) and will make physical climate risk salient. Furthermore, based on previous studies (e.g., Fang and Peress, 2009; Tetlock et al., 2010), Ding and Hou (2015) argue that compared to newspapers, online media coverage is more accessible to retail investors. In addition to the different extents of accessibility between newspapers and online media coverage, the salience of information (e.g., the severity of an extreme weather event) plays a key role when individuals have limited attention associated with their trading decisions (Ramos et al., 2020). Under the salience of climate-related risks, investors are more likely to search for relevant information and account for climate risk (Ghosh and Zhang, 2021). Therefore, retail investors' trading activities are more easily affected by salient information. Hence, retail investors are more likely to associate extreme weather events with an ESG lens (green and brown firms) under the relevant information-searching precondition, thus influencing their trading activity along with the occurrence of unexpected events.

Nevertheless, experimental study by Bassi et al. (2013) generates evidence that weather affects individual risk tolerance through an impact on mood. These authors show that good weather promotes risk-taking behavior. Therefore, if retail investors' trading activity is driven mainly by mood effects, extreme weather events (bad weather) can result in risk aversion. Hence, the relationship between net buying activity and green firms may posit an opposite relationship between pre- and post-extreme weather events. Following these arguments, the first hypothesis is (stated in the alternative form):

Hypothesis 1: *Retail investors will net buy more on green firms after an extreme weather event with unexpected direct damage.*

4. Empirical Design

4.1. Extreme Weather Events

My extreme weather event data is collected from the Spatial Hazard Events and Losses Database (SHELDUS)(ASU Center for Emergency Management and Homeland Security, 2022). The primary source for SHELDUS is the National Centre for Environmental Information (formerly the National Climatic Data Center) monthly Storm Data publications. Recent updates in SHELDUS reporting are more trustworthy due to the modernization of computer systems and enhanced communication within the organization (Vujanovic and Gallagher, 2017), and has been used in many studies (Gall et al., 2009, 2011). Similar to Han et al. (2020), I focus on major events, as in Barrot and Sauvagnat (2016), in which extreme weather events are defined as those that last for less than 30 days and estimated direct damage (crop damage plus property damage) above $ 1 billion (2020 adjusted). From SHELDUS, I identify the severity of each disaster and the affected counties. In total, six types of disasters, flooding, hurricanes, hails, wildfires, tornadoes, and wind, affected 24 counties during the sample period from 2010 to 2020, with 447 firms being affected. Appendix 9.2. lists the extreme weather events classified by county and direct damage. I manually collect the specific date of these events in NOAA since the aggregated data in SHELDUS only provide the data at the monthly level.

4.2. Retail Order Imbalance

Barber and Odean (2008) indicate that trading volume is an indirect measurement of the attention a stock is receiving. Applying this method to retail investor, Boehmer et al. (2021) construct an order imbalance specifically for retail investors. Following the study by Boehmer et al. (2021), I identify the daily-level retail investor's trades and identify retail sells for trades with execution prices that have a sub penny portion between 0.0001 and 0.0040 dollars; for trades which have an execution price between 0.0061 and 0.0099 dollars as retail buys. For each stock i on day t, I have the number of marketable retail buy trades ($Mrbtrd_{it}$) and the number of marketable retail sell trades ($Mrstrd_{it}$), and compute the scaled retail trade order imbalance ($Mroibtrd_{it}$):

$$Mroibtrd_{it} = \frac{Mrbtrd_{it} - Mrstrd_{it}}{Mrbtrd_{it} + Mrstrd_{it}} \tag{1}$$

I do not focus on local retail investors for the following reasons. Previous research indicates that Google Trend is used as attentions from retail investors by several prior studies (Yung and Nafar, 2017; Hamid and Heiden, 2015; Ding and Hou, 2015). Hence, I use three extreme weather events as an example (see Appendix 9.2 for event information). The information is extracted directly from Google Trend, shown in Figure 1. For example, when flooding happened in August-2017 in Harris, most web searches were from Texas, the state of Harris. However, most news searches were from South Dakota state, which is 1,073 miles away from Texas. Therefore, Google Trends in Figure 1 shows that people perceive extreme weather events, even though they are not in an extreme weather event county. Although only suggestive, this implies that when an extreme weather event occurs, people from other states (even very far away) will perceive this information through online media or other information resources. Therefore, I focus on retail investors' trading activities on U.S stocks, regardless of their location.

4.3. Green Firms and Brown Firms

Previous research indicates that stakeholders rely largely on third-party companies to provide ESG ratings and reports to facilitate decision-making (Peloza et al., 2012; De Lucia et al., 2020; Gabzdylova et al., 2009). In the U.S, a sizeable proportion of public firms voluntarily disclose information related to ESG activities and social responsibility (Taylor et al., 2018; Xie et al., 2019). Angeles Lopez-Cabarcos et al. (2020) believes that part of being a high-quality ESG company is the transparency and disclosure of ESG quality, and the quantity of ESG disclosure can represent the quality of ESG disclosure especially under the voluntary disclosure countries. They further argue that the U.S. has minimal ESG disclosure requirements, and companies are more likely to disclose ESG data when they have good ESG performance.

In addition, a survey given by FINRA finds that only a quarter of retail investors can understand ESG investing (Mottola et al., 2022), and retail investors not only do not have direct access to the ESG database but also cannot thoroughly understand ESG content. Therefore, ESG disclosure scores serve as a practical and easily understandable proxy for categorizing green and brown firms as retail investors. Google Trends (see Figure 2) suggests that the search trend of ESG (which are public sources of Bloomberg ESG disclosure information) increases around the dates when an extreme weather event occurs, providing evidence that more individuals (retail investors) start to search/understand what ESG investing is and how it works as a part of firm value. Therefore, I use Bloomberg's ESG disclosure scores to define green and brown firms. The scores range from 0.1 for companies that disclose a minimum amount of ESG data to 100 for those that disclose each of the fields collected by Bloomberg. Finally, a key advantage of using Bloomberg ESG is that the score is tailored to different industry sectors; hence, a company is evaluated using data relevant to its industry. For these reasons, I cut ESG-disclosed firms into high ESG disclosure scores (green firms) and low ESG disclosure score firms (brown firms), grouped by the cross-sectional quintile for each year and industry. Pairs in the top quintile are assigned to the group with green firms and the lowest quintile is assigned to the group with brown firms.

4.4. Sample Construction

My sample starts from the year 2010 because of both the concerns of climate risk and the ESG investing hot up in 2010. I start with retail investors data by following the collecting method given by Boehmer et al. (2021) to obtain daily retail investors trading data with 9,144,155 observations.

I merge extreme weather events with firm information at the county-date level, which allows me to include extreme weather information. Next, I add the yearly Bloomberg ESG disclosure score to ensure that the final sample includes all firms with ESG disclosure scores. Since only 909 firms disclosed ESG information with 7919 observations over the past 10 years, the number of my sample size dropped to 95,535. I then add firms' financial information to generate the control variables. I exclude all firms that are not headquartered in the U.S. In more detailed ESG screen analyses, utility firms usually have low environmental scores along with high Social and Governance scores, whereas financial firms normally have high environmental scores with low social and governance scores (Alessandrini et al., 2021). In addition, ESG performance disclosure shows a significant difference between financial and non-financial industries (Gholami and Sands, 2022); therefore, I exclude utility and financial firms with SIC codes between 4910 to 4939 and 6000 to 6999, respectively. After removing firms in the financial or utility industry, and firms with missing financial information that needs to be controlled, I finally get 29,394 observations for the main analysis from 2010 to 2020. The sample construction is presented in Table 1.

4.5. Methodology

I examine the effect of extreme weather events on retail investors' trading activity through different levels of ESG disclosure using a difference-in-differences estimation. My main specification is in the following:

$$\begin{aligned} &OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \\ &\beta_4 Brown_{i,t} + \beta_5 Brown_{i,t} * Post + \gamma X_{i,t} + Fixedeffect + \epsilon_{it} \end{aligned} \tag{2}$$

where green and brown are dummy variables that indicate whether a firm has a high (uppermost quintile) or low (lowest quintile) ESG disclosure score for each year and industry. Post is the time variable, which equals one in the days after and includes the day of an extreme weather event, and zero otherwise. The day of the post is defined as follows: First, the mean duration of extreme weather events is 4.7 days, and the maximum duration is 18 days. In addition, research on retail investor attention usually focuses on a short-term horizon of approximately one week (Barber and Odean, 2008; Wang et al., 2018). Therefore, I begin my analysis by focusing on the short horizon and embedding seven calendar days (one week) and fourteen calendar days (two weeks) post in the main analysis. The estimate of β_3 is a difference-in-difference estimate that captures the change in retail investors' order imbalance of high ESG score firms from before to after extreme weather events to see whether retail investors trade high ESG firms more after extreme weather events.

X represents the control variables, including firm size, leverage, return on assets, loss, quick ratio, momentum, and market-to-book ratio (mtb) (Chui et al., 2022; Kaiser, 2020; Hirshleifer et al., 2008). Following the procedure proposed by (Guimaraes and Portugal, 2010) to fit models with high-dimensional fixed effects, I use industry fixed effects and year-month fixed effects to control for time-invariant differences among firms and across the year-month level. All firm-level variables are winsorized at the 1st and 99th percentiles. All standard errors are clustered according to the industry and year-month levels.

5. Results

5.1. Descriptive Statistics

Panel A of Table 2 reports the descriptive statistics of the variables in the main sample. Since the sample is constructed by including all firms with ESG scores, the mean and median values of ROA, for example, are lower.[10] From this perspective, firms with ESG disclosure scores have lower ROA, particularly those with low ESG disclosure scores. Panel C of Table 2 compares the trading activities and characteristics of the high- and low-ESG firms. In general, the size of high ESG firms is larger than that of low ESG score firms, along with higher ROA and leverage.

5.2. Main Result: Retail Investor Trading

I test the hypothesis and report the estimates of the main results in Table 3. Columns (1) and (2) show the results without Post (no extreme weather event), which enables the examination of retail investors' trading activity on green and brown firms. Column (1) shows the estimates with fixed effects and no control variables and Column (2) reports the estimates with fixed effects and control variables. The results show that retail investors do not trade differently for green and brown firms. I then add Post by merging with extreme weather events data, including the days before and after an extreme weather event. Therefore, the results in Columns (3) and (4) show the trading activity of retail investors after an extreme weather event. The coefficient on $Green * Post$ in Column (3) is positive and statistically significant at the 1 per cent level, suggesting that retail investors net buy more green firms after an extreme weather event. This result in Column (4) suggests that retail investors do not significantly change their trading activity on brown firms after extreme weather events. As Column (5) shows, net buying trading activity is mitigated after 14 days. Together, the results suggest that extreme weather events make the climate related risk salient to retail investors, and retail investors net

[10] Therefore, I test the descriptive statistics before merging with only firms with an ESG disclosure score from Bloomberg (untabulated). The mean value of ROA is -0.042 (untabulated), which is comparable to that in previous studies (Larrain et al., 2017).

buy more on green firms within the period[11] of an extreme weather event.

6. Additional Analyses

6.1. Cash Flow: Do Green Firms Perform Better after Extreme Weather Events?

To the extent that extreme weather events affect cash flows, this study provides a unique opportunity to investigate the role of ESG information in managing cash flow shocks. Extreme weather events are measured over a relatively short interval and may destroy a region's infrastructure and affect a firm's long-run growth prospects. Brown et al. (2021) examines whether there are weathering cash flow shocks using the event, which they call 'abnormal snow'. They find a negative and statistically significant relationship[12] between abnormal snow and corporate cash flows. This issue should raise investor awareness, even if firms are not affected by the damage. Therefore, after extreme weather events occur, a good ESG profile may help firms survive more quickly via the cash flow channel than firms with poor ESG profiles. Pastor et al. (2021) predicts that customers are more likely to buy sustainable products. Therefore, cash flows may increase because of the increasing revenue. To examine this prediction, I construct the following regression to test the impact of cash flow:

$$\begin{aligned} CashFlow_{i,q} =& \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 Brown_{i,t} + \\ & \beta_5 Brown_{i,t} * Post + \gamma X_{i,t} + FixedEffect + \epsilon_{it} \end{aligned} \tag{3}$$

Following the study given by Brown et al. (2021), cash flow is calculated as the sum of operating income, depreciation, and amortization to compute the EBITDA. I then scale EBITDA by total $assets_{t-1}$ to compute cash flow. Each extreme event defined in this study was manually matched to its latitude and longitude. I use the latitude and longitude of a county in Google search engine if there is no recorded latitude nor longitude

[11] The mean of duration is 4.7 days and the maximum duration of an extreme weather event in this study is 18 days.

[12] Although a negative relation between cash flows and severe winter weather can be rationalized across a wide range of industries, the magnitude of the relation likely varies by industry.

of a specific event. The interaction variable $Green * Post$ captures the difference between green and non-green firms before and after extreme weather events. The results are presented in Table 4. For firms with ESG disclosure scores, the cash flow of green firms is positive and statistically significant for 1 quarter and 2 quarter after an extreme weather event. Meanwhile, brown firms have a negative and statistically significant relationship with further cash flow.

To understand the reason for the increasing cash flow and to examine the prediction of customers, I use revenue because it is a driver of cash flow(Rao and Bharadwaj, 2008). I do not find a statistically significant relationship between revenues and $Revenue * Post$. The results suggest that increasing cash flow may not relate to customer preferences, consistent with the study by Ardia et al. (2020), who examine climate change concerns in the media and the impact on stock prices. Instead of increased revenue, they find that the increase in climate concerns is associated with the discount rate.

As a measurement of efficiency, return on assets (ROA) provides information about how much profit a company can generate from its assets; hence, it can suggest whether green firms will be better with extreme weather events. Therefore, I test the impact of extreme weather events on ROA between green and brown firms. The results show that, after an extreme weather event, green firms are more efficient in earning profits from their assets, as shown by the positive and statistically significant relationship between ROA and $Green * Post$. The increasing ROA suggests that green firms are better able to withstand extreme weather events.

6.2. Why Do Retail Investors Buy More Green Firms after Extreme Weather Events?

Based on the results in Section 6.1, green firms have a better cash flow and ROA after extreme weather events. Therefore, I further test whether retail investors only net buy more on green firms with better cash flow. To understand this, I run the following two regressions:

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Dowell_{i,t} + \beta_2 Post + \beta_3 Dowell_{i,t} * Post + \gamma X_{i,t} + FixedEffect + \epsilon_{it} \tag{4}$$

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 Dowell_{i,t} + \beta_5 Dowell_{i,t} * Post + \beta_6 Dowell_{i,t} * Green_{i,t} + \beta_7 Dowell_{i,t} * Green_{i,t} * Post + \gamma X_{i,t} + FixedEffect + \epsilon_{it} \tag{5}$$

where Dowell is a dummy variable that equals one if firms have a better cash flow[13] than the average cash flow of the industry in the quarter of an extreme weather event, and zero otherwise. Equation (4) tests whether retail investors buy more firms with better cash flow after extreme weather events, and Equation (5) tests whether retail investors favor green firms with better cash flow after extreme weather events. Table 6 presents the results. Results do not find a significant relationship between OrderImbalance and $Dowell * Post$ nor between OrderImbalance and $Dowell * Post * Green$. These results suggest that retail investors' trading activity after extreme weather events is not driven by the extent of cash flow. Furthermore, the insignificant coefficient of $Dowell * Post * Green$ suggests that retail investors' preference for buying more green firms is driven by the salient risk of extreme weather events.

6.3. Weather Exposure on the Annual Report

In addition to the third-party measurement of ESG-related information, firms report their weather exposure in annual reports. High weather exposure means that a firm's average exceeds the sample mean average in its annual report. Following the study by Nagar and Schoenfeld (2022),[14] high weather exposure should be used in the prior year. Therefore,

[13]Cash flow is calculated by using EBITDA, and by using operation cash flows.

[14]I appreciate to Professor Jordan Schoenfeld, who kindly share the weather exposure data on his personal website (see: http://www.jordanschoenfeld.com/).

I run the following regression:

$$
\begin{aligned}
&Mroibtrd_{i,d} = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 HighExpo_{i,t} + \\
&\beta_5 HighExpo_{i,t} * Post + \beta_6 HighExpo_{i,t} * Post * Green_{i,t} + \gamma X_{i,t} + \\
&FixedEffect + \epsilon_{it}
\end{aligned} \tag{6}
$$

The coefficient on $HighExpo * Post * Green$ represents whether retail investors will net buy more on high ESG firms after extreme weather events even though these firms are under high weather exposure. The results are shown in Table 7. Column (1) shows that the coefficient of $HighExpo * Post$ is negative and statistically significant, suggesting that retail investors would like to sell more on firms with high weather exposure in the annual report after extreme weather events. Meanwhile, the positive relationship between $HighExpo * Post * Green$ and Mroibtrd shows that firms with high ESG disclosure score (green firms) mitigate the retail investors' selling activity of firms with high weather exposure after extreme weather events.

6.4. Firms in Affected Area

Next, I test the retail trading activity of affected firms within certain miles of extreme weather event counties. The regression is as follows:

$$
\begin{aligned}
&Mroibtrd_{i,d} = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 Affected_{i,t} + \\
&\beta_5 Affected_{i,t} * Post + \beta_6 Affected_{i,t} * Green_{i,t} + \beta_7 Affected_{i,t} * Post * Green_{i,t} + \\
&\gamma X_{i,t} + FixedEffect + \epsilon_{it}
\end{aligned} \tag{7}
$$

Affected equals one if firms within 300 miles[15] of the extreme weather event county. The estimate of $Brown * Post * Affected$ in Column (2) of Table 8 is negative and statistically significant at the 5 percent level when the post period is two weeks, and I observe no significant results when the post period is one week. The results imply that after extreme weather events, retail investors are likely to first net buy more green firms in general and

[15] Results hold consistent by changing 300 miles to 200, 250 miles.

do not focus specifically on firms within the disaster area.

6.5. Social Media Presence

Retail investors' attention could be affected by proxies related to coverage on social media (Ding and Hou, 2015), and retail investors may naturally have more attention on firms with a high social media presence and a good ESG profile. The results in Figure 1 have suggested that individuals search for information via online media. From this perspective, the relationship for high ESG firms with more retail buying after weather events may be that high social media firms have more retail buying after extreme weather events. Therefore, controlling a social media presence proxy would be helpful in addressing this concern. I then conduct a variable $HighPresence$ to indicate whether a firm has high social media exposure using the Twitter API. Many firms regard Twitter as an important social media agency that conveys information and influence people (Oztamur et al., 2014). Furthermore, retail investors rely more on Twitter compared with institutional investors (Rakotomavo, 2011; Behrendt et al., 2018). The inclusion of firm social media presence can decrease the possibility that the results are driven by high social media presence, and the interaction between social media presence and unexpected extreme weather events. First, I manually collect firms twitter handles. Second, I use Twitter API to collect the number of tweets per account.[16] I use the average number of tweets a firm made to represent the extent of social media presence. I define high social media presence as a firm that generates more tweets than the average by industry. The regression is in the following:

$$\begin{aligned} &Mroibtrd_{i,d} = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 HighPresence_{i,t} + \\ &\beta_5 HighPresence_{i,t} * Post + \beta_6 Brown_{i,t} + \beta_7 Brown_{i,t} * Post + \beta_8 X_{i,t} + \\ &FixedEffect + \epsilon_{it} \end{aligned} \tag{8}$$

I add $HighPresence$ as a control variable in Column (1). I add $HighPresence * Post$ in Column (2) to control the impact of high social media presence after an unexpected

[16] Each firm can extract 3200 tweets at most, and this amount covers most firms' 10-year interval.

extreme weather event. Both results in Table 9 are consistent with the main result in Table 3.

7. Robustness Tests

7.1. Does Abnormally Long-Duration Capture Retail Investors Attention?

To better understand what drives retail investors' attention, this section examines extreme weather events with abnormally long durations. Following the study by Griffin et al. (2021), I calculate the abnormally long duration of extreme weather events as the uppermost quintile of the residual value of the mean event duration over the past three years and the current fiscal year. The calculation of the abnormally extreme weather day duration is the residual from the following prediction model:

$$\mathrm{L}ogdaycnt = Logdaycntpast + \epsilon_{it} \tag{9}$$

where Equation (9) uses the log average number of extreme weather event days of an event over the past three years (Logdaycntpast) to predict the number of extreme weather days in year t: The abnormally long duration is the uppermost quintile of the residual value. A detailed definition is provided in Appendix 9.1. In total, there are 13 types of disasters and 177 extreme weather events from 2010 to 2020, and there are two overlapping events. I calculate the impact of retail trading activity using the same time interval as in the main test. If an abnormally long duration captures retail investors' attention, the interaction variable $Green * Post$ is expected to be positive and statistically significant. Table 10 presents the results.

The results for both the one-week and two-week periods are insignificant, suggesting that retail investors do not trade differently between green and brown firms when an extreme weather event is defined as an abnormally long duration. Combined with the main results in Table 3, results suggest that investors are salient to direct damages that climate weather brings and care about how these weather events could potentially affect firms.

7.2. Alternative Measurement: Trading Volume

I use trading volume as an alternative measure of the retail order imbalance. Volume is calculated as the total buy and sell of a firm per day, divided by the total volume per month.

The results are consistent with the main result, that is, retail investors trade more on green firms after an extreme weather event. Furthermore, combined with the main result, increasing number of trading volume is driven by more net buying activity.

7.3. Environmental, Social and Governance Dimension

To discern whether the net buying behavior of retail investors in green firms originates from a particular dimension (Environmental, Social, or Governance) or is solely associated with the broader ESG concept, I investigate the net buying activity of green firms after extreme weather events when these firms fall within the uppermost quintile of each dimension. These findings indicate that retail investors tend to increase their net buying activity for green firms when these firms rank within the uppermost quintile of high environmental disclosure scores. There is no empirical evidence to indicate that the net buying activity of these green firms after extreme weather events is related to the uppermost social disclosure score quintile or governance disclosure quintile. Therefore, the results suggest that in addition to ESG disclosure information, retail investors focus particularly on environment-related information after extreme weather events.

7.4. Different Exogenous Shock: Covid-19

In contrast to extreme weather events, Covid-19 is regarded as an economic shock. Previous research suggests that the decline of sustainability stocks [17] among individual investors is sharper than fund flows because individual investors are more sensitive to in-

[17] In my study, it is called green firms.

come shocks due to Covid-19 (Dottling and Kim, 2022). I, therefore, define the Covid-19 shock as the period between 21st-Feb-2020 and 25th-Apr-2020, and the pre-Covid period from 1st-Jan-2020 to 20th-Feb-2020. The regression is as follows:

$$\begin{aligned} &Mroibtrd_{i,d} = \alpha + \beta_1 Green_{i,t} * Covid + \beta_2 Covid + \beta_3 Green_{i,t} + \beta_4 Brown_{i,t} + \\ &\beta_5 Brown_{i,t} * Covid + \gamma X_{i,t} + FixedEffect + \epsilon_{it} \end{aligned} \tag{10}$$

I find a negative and statistically significant coefficient on Green*Covid, indicating that retail investors sell more on green firms during the Covid crisis compared to pre-Covid. This result suggests that, in contrast to extreme weather events, high-ESG firms do not have luster among retail investors during the Covid crisis. Meanwhile, retail investors trading activity is driven by specific types of crisis.

7.5. Randomlized Time Indicator

Other exogenous policies, such as positive macroeconomic news, may lead to greater net buying activity. Failure to account for such information may lead to a spurious relationship between extreme weather events and changes in retail trading activities. Although high-frequency data within a short event window, as used in the main model, mitigates this issue, I execute a placebo check to further alleviate such concerns. First, I randomize time variable (Post). I then re-estimate Equation 2 after replacing the post with randomized time (time variable).

This process is repeated 500 times. Only six estimates have a t-value greater than the main results among the 500 repeated times. This represents 1.2% of the total permutations, which is below the conventional significance level (5%). Therefore, the relationship between net buying activity and the salience of climate-related risk (after an extreme weather event) is not spurious.

8. Conclusion

ESG investing has grown rapidly over the last decade with debates on investor preferences. Many studies have examined ESG from the perspective of fund managers and institutional investors, whereas the demand perspective of retail investors has been much less extensively explored. This study examines whether retail investors' trading activities of green firms differ before and after extreme weather events. Using a difference-in-differences analysis, I find that retail investors will net buy more on green firms after extreme weather events, and this trend starts to mitigate along with the end of the extreme weather event. Therefore, the results suggest that retail greenness demand is sensitive to extreme weather events. The results are robust to controlling for firms' social media presence and weather exposure in annual reports along with other robustness checks. My results highlight retail investors' trading activity in green firms and examine extreme weather events as shocks that raise awareness of climate-related risks. Hence, this study has implications for the understanding of the importance and salience of environmental issues.

To understand why retail investors favor green firms after extreme weather events, I test the cash flow channel and retail investors trading activity for green firms that have better cash flows. Results suggest that retail investors do not net buy more on green firms because they have a better financial performance. Along with other tests, my study supports the argument that the increasing net buying activity on green firms is related to the salient risk. Meanwhile, as green firms' cash flow and ROA are temporary following extreme weather events, I recommend that regulators and policymakers should consider providing more support to green firms, which may have useful implications for the importance of environmental issues.

Figure 1: **Google Trends - Web Search and News Search**

This figure reports the google trends of the top three extreme weather events that influence most firms over the past 10 years. I extract the news search and web search two-week before and two-week after extreme weather events. When these event happen, the most frequent search of "Hail","Flooding", and "Wildfire" are not always from extreme weather event county, or even very far away.

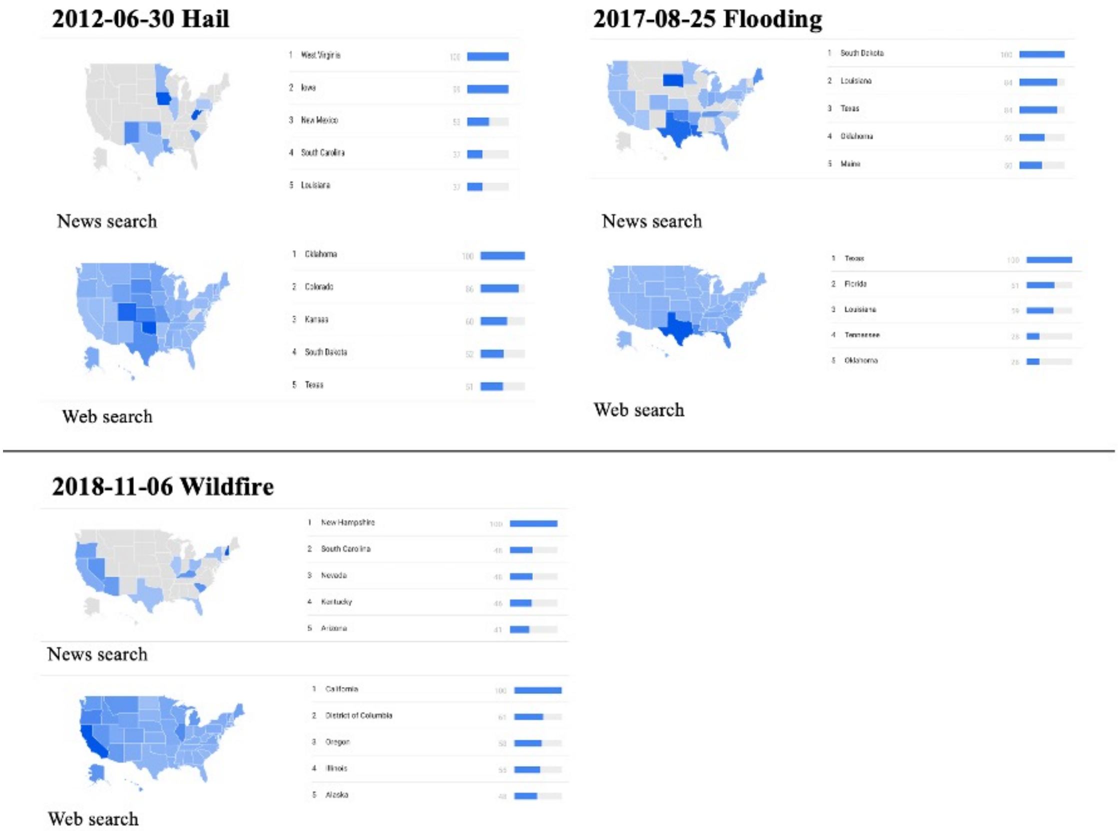

Figure 2: **Google Trends – ESG Keyword Search**

This figure plots an example about whether Google searching on term 'ESG' increases after an extreme weather event, here is the flood on the 12th August 2016.

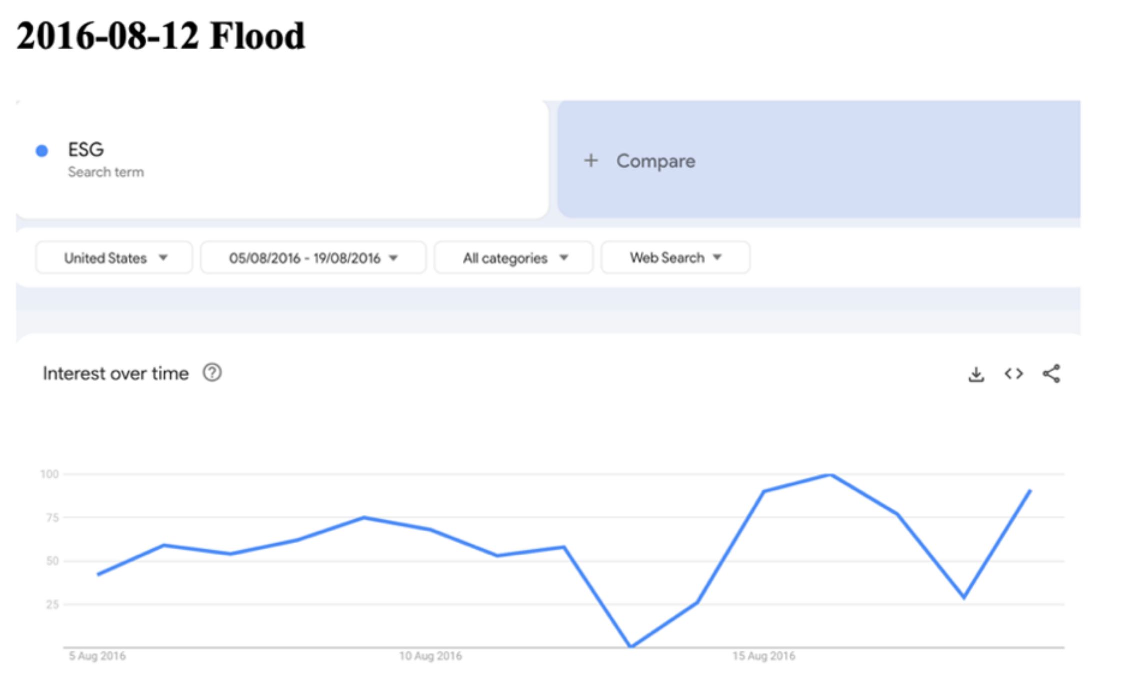

Figure 3: **Placebo Test**

This figure plots the placebo test by randomized post group to test the possibility that the relationship between extreme weather events and the change in retail trading activity is spurious. Only 6 among 500 times more than the t-value in main regression (1.2%).

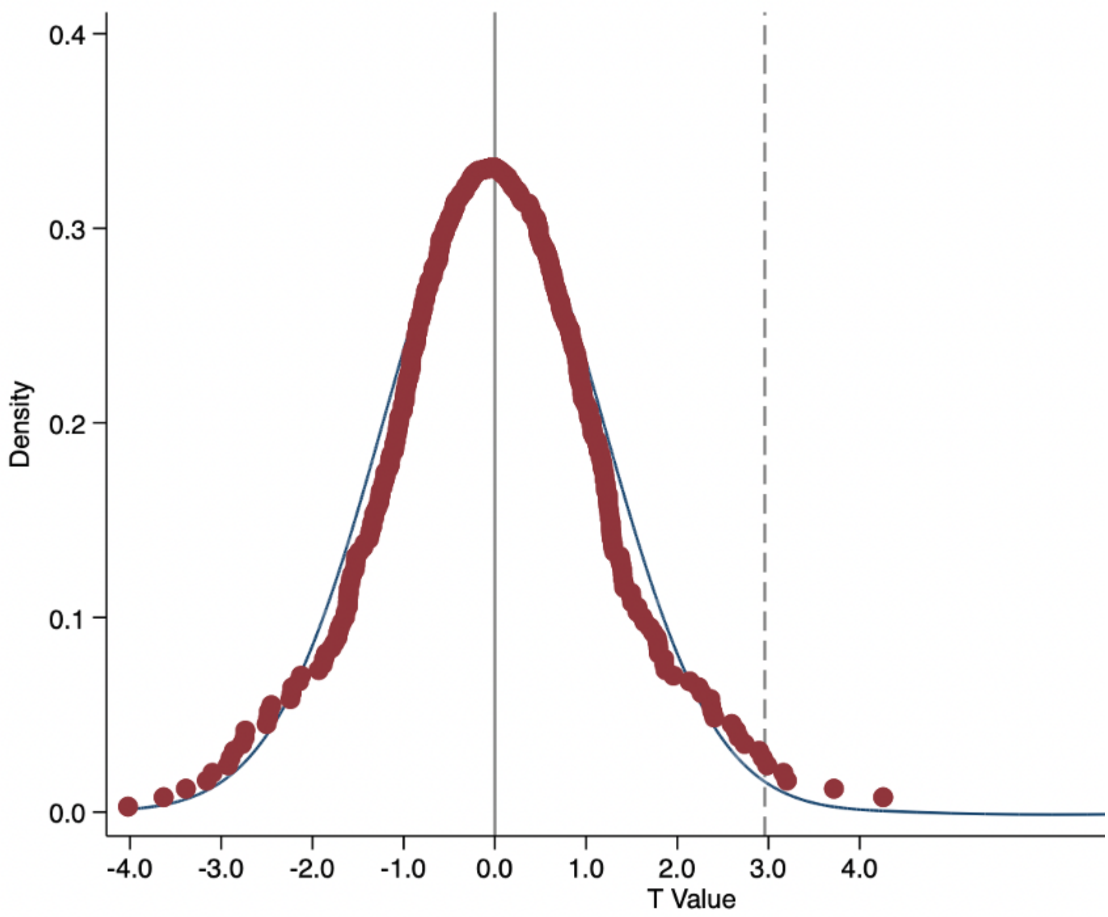

Table 1: **Sample Construction**

	Number of observations
Daily retail investor data from 2010 to 2020	9,144,155
Less: trading days that are not in the pre 7 days nor post 7 days	
extreme weather event period	(8,444,356)
Less: Observations without ESG disclosure score from Bloomberg	(604,264)
Less: Firms miss financial information from Compustat	(35,925)
Less: Variables with no observation	(30,216)
Observations in the final main regression	29,394

Table 2: **Descriptive Statistics**

Retail Investor						
Panel A: Descriptive Statistics [-7d, +7d]						
Variable	Obs	Mean	P25	Median	P75	SD
Mroibtrd	29,394	-0.026	-0.334	-0.019	0.274	0.511
Volume	29,394	0.131	0.051	0.091	0.159	0.137
Size	29,394	5.175	3.903	5.017	6.204	1.770
Leverage	29,394	0.219	0.000	0.106	0.299	0.438
ROA	29,394	-0.220	-0.311	-0.033	0.045	0.513
Loss	29,394	0.577	0.000	1.768	3.919	5.490
Quick	29,394	3.791	1.107	2.029	3.894	10.192
Momentum	29,394	-0.098	-1.000	0.000	1.000	0.942
Mtb	29,394	3.420	1.107	2.029	3.894	10.192
Panel B: Descriptive Statistic [-14d, +14d]						
Variable	Obs	Mean	P25	Median	P75	SD
Mroibtrd	53,691	-0.025	-0.333	-0.016	0.273	0.512
Volume	53,691	0.093	0.030	0.057	0.104	0.132
Size	53,691	5.181	3.905	5.019	6.204	1.774
Leverage	53,691	0.219	0.000	0.106	0.299	0.436
ROA	53,691	-0.220	-0.311	-0.033	0.045	0.494
Loss	53,691	0.577	0.000	1.000	1.000	0.494
Quick	53,691	3.790	0.982	1.758	3.919	5.481
Momentum	53,691	-0.093	-1.000	0.000	1.000	0.942
Mtb	53,691	3.393	1.109	2.033	3.901	10.133
Panel C: Mean of Green and Other Firms						
Variable	Green			Other		
	No.obs	Mean		No.obs	Mean	Difference
Mroibtrd	6,303	-0.030		23,091	-0.024	-0.006
Volume	6,303	0.135		23,091	0.130	0.005***
Size	6,303	6.363		23,091	4.851	1.512***
Leverage	6,303	0.251		23,091	0.210	0.040***
ROA	6,303	-0.053		23,091	-0.265	0.212***
Loss	6,303	0.428		23,091	0.617	-0.189***
Quick	6,303	2.103		23,091	4.252	-2.149***
Momentum	6,303	-0.088		23,091	-0.101	-0.013***
Mtb	6,303	2.603		23,091	3.643	1.040***

Table 3: **Main result: ESG Disclosure Score from Bloomberg**

This table presents results on the difference-in-difference regression on green firms. Order Imbalance is calculated as shown in Equation 1 at the daily level. The positive coefficient indicates retail investors' net buying, and the negative indicates selling. Green firms are those firms with high ESG disclosure scores (uppermost quintile), and Brown firms are those firms with low ESG disclosure scores (lowest quintile). Post is a time variable, which means the days after extreme weather events. For Col (3) and Col (4), post equals one within 7 days after an extreme weather event. For Col (5), post equals one within 14 days after an extreme weather event happening.

OrderImbalance(Mroibtrd)	No extreme		Post = 7 days		Post=14 days
	(1)	(2)	(3)	(4)	(5)
Green	-0.001	-0.004	-0.034***	-0.021***	-0.001
	(-0.03)	(-0.97)	(-3.01)	(-2.96)	(-1.25)
Brown	0.004	0.004		0.001	0.006
	(1.14)	(1.23)		(0.08)	(0.71)
Post			-0.012**	-0.013*	-0.001
			(-1.97)	(-1.77)	(-0.03)
Green*Post			0.029***	0.029***	0.008
			(2.96)	(2.78)	(1.27)
Brown*Post				0.001	-0.002
				(0.06)	(-0.20)
Size		0.003*	0.006**	0.006**	0.003
		(1.89)	(2.51)	(2.00)	(1.22)
Leverage		-0.001	0.005	0.005	0.000
		(-0.30)	(0.94)	(0.91)	(0.05)
ROA		-0.002	-0.006	-0.006	-0.004
		(-0.61)	(-0.71)	(-0.70)	(-0.39)
Loss		-0.003	-0.004	-0.004	0.006
		(-0.83)	(-0.61)	(-0.58)	(1.20)
Quick		0.001	-0.002	-0.002	-0.006
		(0.58)	(-0.31)	(-0.31)	(-0.87)
Momentum		-0.001	0.017	0.002	0.002
		(-0.73)	(0.42)	(0.41)	(1.13)
Mtb		0.001	0.001	0.001	-0.000
		(0.66)	(0.39)	(0.37)	(-0.07)
N	379,397	379,397	29,394	29,394	53,691
Industry fixed effect	Y	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y	Y
Eventcounty fixed effect	Y	Y	Y	Y	Y
$Adj R^2$	0.001	0.002	0.001	0.001	0.001

Table 4: **Cash Flow**

This table tests the cash flow of green firms and brown firms after extreme weather event. Post equals one if there is an unexpected extreme weather event in the current quarter and no extreme weather events over the past four quarter and next four quarter.

$$
\begin{aligned}
CashFlow_{i,q} = &\alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 Brown_{i,t} + \beta_5 Brown_{i,t} * Post + \\
&\beta_6 X_{i,t} + FixedEffect + \epsilon_{it}
\end{aligned}
$$

Cash Flow	Post = 1Q	Post = 2Q	Post = 3Q	Post = 4Q
	(1)	(2)	(3)	(4)
Green	-0.040**	-0.034***	-0.023*	-0.027**
	(-2.15)	(-2.78)	(-1.86)	(-2.09)
Brown	0.027**	0.010	0.003	-0.001
	(2.44)	(1.41)	(0.41)	(-0.20)
Post	-0.012	-0.000	0.003	-0.007
	(-1.07)	(-0.05)	(0.39)	(-0.71)
Green*Post	0.032*	0.024**	0.012	0.016
	(1.93)	(2.10)	(1.14)	(1.44)
Brown*Post	-0.032***	-0.013**	-0.004	0.001
	(-3.66)	(-2.16)	(-0.61)	(0.15)
Size	0.009**	0.024***	0.024***	0.024***
	(2.36)	(5.30)	(5.32)	(5.32)
Leverage	-0.054***	-0.052***	-0.052***	-0.052***
	(-3.47)	(-3.18)	(-3.18)	(-3.17)
ROA	0.871***	0.859***	0.859***	0.859***
	(19.08)	(18.62)	(18.62)	(18.60)
Loss	-0.037***	-0.040***	-0.040***	-0.040***
	(-3.03)	(-2.80)	(-2.79)	(-2.80)
Quick	-0.003*	-0.004**	-0.004**	-0.004**
	(-1.71)	(-2.03)	(-2.02)	(-2.02)
N	13,271	13,964	13,964	13,964
Industry fixed effect	Y	Y	Y	Y
Time fixed effect	Y	Y	Y	Y
Affectedcounty fixed effect	Y	Y	Y	Y
$AdjR^2$	0.58	0.57	0.57	0.57

Table 5: **Return on Assets(ROA)**

ROA	Post = 1Q	Post = 2Q
	(1)	(2)
Green	-0.054***	-0.046**
	(-2.94)	(-2.28)
Brown	-0.015	-0.011
	(-1.10)	(-0.58)
Post	-0.008*	-0.004
	(-1.75)	(-1.00)
Green*Post	0.021**	0.013
	(2.19)	(1.10)
Brown*Post	-0.008**	-0.012
	(-2.20)	(-1.32)
Size	0.036***	0.036***
	(5.55)	(5.65)
Loss	-0.106***	-0.106***
	(-9.10)	(-9.08)
Quick	0.009***	0.009***
	(7.88)	(6.60)
N	13,271	13,964
Industry fixed effect	Y	Y
Time fixed effect	Y	Y
$Adj R^2$	0.32	0.32

Table 6: **Why Do Retail Investors Buy More Green Firms after Extreme Weather Events?**

This table tests whether retail investors trading activity after extreme weather events is related to the performance of firms. Column(1) tests whether retail investors net buy more on firms that have better cash flow compared with the mean value of its industry after extreme weather events, and Column(2) tests whether the net buying activity in green firms is due to these green firms having better cash flow following extreme weather events. Regressions are in the following:

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Dowell_{i,t} + \beta_2 Post + \beta_3 Dowell_{i,t} * Post + \gamma X_{i,t} + FixedEffect + \epsilon_{it}$$

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 Dowell_{i,t} + \beta_5 Dowell_{i,t} * Post + \beta_6 Dowell_{i,t} * Green_{i,t} + \beta_7 Dowell_{i,t} * Green_{i,t} * Post + \gamma X_{i,t} + FixedEffect + \epsilon_{it}$$

OrderImbalance(Mroibtrd)	Firms that perform better	Green firms that perform better
	(1)	(2)
Dowell	-0.004	-0.015
	(-0.32)	(-0.98)
Post	0.003	-0.007
	(0.04)	(-1.02)
Dowell*Post	-0.005	0.001
	(-0.35)	(0.01)
Green		-0.063***
		(-3.55)
Green*Dowell		0.062**
		(1.97)
Green*Post		0.045*
		(1.77)
Green*Dowell*Post		-0.033
		(-0.85)
Size	0.005**	0.006**
	(2.10)	(2.48)
Leverage	0.023***	0.024***
	(2.83)	(2.68)
ROA	-0.004	0.004
	(-0.12)	(0.10)
Loss	-0.006	-0.006
	(-0.58)	(-0.58)
Quick	0.002*	0.002
	(1.79)	(0.82)
Momentum	0.005	0.004
	(0.92)	(0.82)
Mtb	0.003	0.003
	(0.81)	(0.76)
N	21,758	21,758
Industry fixed effect	Y	Y
Time fixed effect	Y	Y
Affectedcounty fixed effect	Y	Y
$AdjR^2$	0.005	0.005

Table 7: **Weather Exposure on the Annual Report**

Weather exposure on the annual report is the frequency of 'weather' mentioned in the annual report. The higher disclosure of weather, the more frequently the term 'weather' is mentioned in the annual report, representing firms' business exposure to weather.

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 HighExpo_{i,t} + \beta_5 HighExpo_{i,t} * Post + \beta_6 HighExpo_{i,t} * Post * Green_{i,t} + \beta_7 X_{i,t} + FixedEffect + \epsilon_{it}$$

OrderImbalance(Mroibtrd)	Post = 7 days	Post = 14 days
	(1)	(2)
HighExpo	0.043**	0.041***
	(2.50)	(3.69)
Green	0.003	0.001
	(0.03)	(0.84)
HighExpo*Green	-0.088**	-0.070**
	(-2.42)	(-2.45)
Post	-0.004	-0.001
	(-0.50)	(-0.03)
HighExpo*Post	-0.042**	-0.021**
	(-2.32)	(-2.13)
Green*Post	-0.006	-0.015*
	(-0.70)	(-1.74)
HighExpo*Post*Green	0.075**	0.045**
	(2.51)	(2.41)
Size	0.006	0.005
	(1.65)	(1.25)
Leverage	0.003	-0.001
	(0.33)	(-0.01)
ROA	-0.003	-0.002
	(-0.22)	(-0.17)
Loss	0.004	0.013*
	(0.43)	(1.77)
Quick	-0.001	-0.001
	(-1.33)	(-1.21)
Momentum	0.005	0.005
	(0.82)	(1.37)
Mtb	0.001	0.001
	(0.32)	(0.31)
N	20,996	37,976
Industry fixed effect	Y	Y
Time fixed effect	Y	Y
Affectedcounty effect	Y	Y
$AdjR^2$	0.001	0.001

Table 8: **Firms in Affected Area**

In this table, I test affected firms within certain miles of extreme weather event county, to see whether retail investors pay particular attention on firms that are near to the extreme weather event county. Affected firms are firms that are near the disaster area but are not within the disaster area. The results hold consistent by changing to different distance (200, 250, 300 miles) between firms and extreme weather event county. Below table shows the result when the distance between firms and extreme weather event county is 300 miles.

OrderImbalance(Mroibtrd)	Post = 7 days	Post = 14 days
	(1)	(2)
Green	-0.037***	-0.017
	(-3.07)	(-1.31)
Brown	0.006	0.003
	(0.37)	(0.35)
Post	-0.009	0.000
	(-0.84)	(0.01)
Affected	-0.015	-0.177
	(-0.63)	(-0.92)
Green*Post	0.036**	0.016
	(2.43)	(1.53)
Green*Affected	0.044	0.064**
	(1.07)	(2.24)
Post*Affected	0.003	-0.006
	(0.09)	(-0.25)
Green*Post*Affected	-0.013	-0.033
	(-0.24)	(-0.99)
Brown*Post	-0.005	-0.001
	(-0.25)	(-0.08)
Brown*Affected	0.004	0.039
	(0.07)	(1.21)
Brown*Post*Affected	-0.009	-0.078**
	(-0.15)	(-2.10)
Size	0.005*	0.004
	(1.93)	(1.28)
Leverage	0.007	0.001
	(1.07)	(0.15)
ROA	-0.005	-0.006
	(-0.74)	(-0.64)
Loss	-0.008	0.002
	(-1.02)	(0.45)
Quick	-0.002	-0.001
	(-0.46)	(-0.40)
Momentum	0.001	0.003
	(0.24)	(0.96)
Mtb	0.001	-0.001
	(0.29)	(-0.34)
N	26,294	48,054
Industry fixed effect	Y	Y
Time fixed effect	Y	Y
Eventcounty fixed effect	Y	Y
$AdjR^2$	0.001	0.001

Table 9: **The Impact of Social Media Presence**

Firms with high social media presence may also leads to more trading for retail investors. Therefore, social media presence may be a mediator of the relationship between order imbalance and $Green * Post$. Therefore, I control for the $HighPresence$ by calculating the average tweets a firm made and regard the ones that above the mean value as the $HighPresence$, equals to 1, otherwise 0. The result holds consistent after trying median.

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Green_{i,t} + \beta_2 Post + \beta_3 Green_{i,t} * Post + \beta_4 HighPresence_{i,t} + \beta_5 HighPresence_{i,t} * Post + \beta_6 Brown_{i,t} + \beta_7 Brown_{i,t} * Post + \beta_8 X_{i,t} + FixedEffect + \epsilon_{it}$$

OrderImbalance(Mroibtrd)	(1)	(2)
Green	-0.033***	-0.033***
	(-2.88)	(-2.76)
Post	-0.012*	-0.20**
	(-1.77)	(-2.52)
Green*Post	0.029***	0.029***
	(2.74)	(2.67)
HighPresence	0.011	0.037
	(1.52)	(0.46)
HighPresence*Post		0.014*
		(1.81)
Brown	0.018	0.001
	(0.14)	(0.09)
Brown*Post	0.001	0.002
	(0.06)	(0.11)
Size	0.056*	0.006*
	(1.71)	(1.71)
Leverage	0.004	0.004
	(0.68)	(0.67)
ROA	-0.005	-0.005
	(-0.53)	(-0.54)
Loss	-0.003	-0.003
	(-0.46)	(-0.45)
Quick	-0.003	-0.000
	(-0.37)	(-0.38)
Momentum	0.002	0.002
	(0.57)	(0.56)
Mtb	0.000	0.000
	(0.35)	(0.35)
N	29,394	29,394
Industry fixed effect	Y	Y
Time fixed effect	Y	Y
Eventcounty fixed effect	Y	Y
$AdjR^2$	0.001	0.001

Table 10: **Abnormally Long Duration of Extreme Weather Event**

To understand what drives retail investors attention, I examine extreme weather events that has abnormally long duration in this table. Abnormally long duration is calculated as the uppermost quintile of the residual value in the following regression:

Logdaycnt = Logdaycntpast + ϵ_{it}

Logdaycntpast is the log average number of extreme weather event days of an event over the past three, year and logdaycnt is the log average number of extreme weather days in year t. The abnormally long duration is the uppermost quintile of the residual value. Post is the time variable, indicating the days after an extreme weather event with abnormally long duration.

OrderImbalance(Mroibtrd)	Post = 7 days	Post = 14 days
	(1)	(2)
Green	-0.010	-0.012*
	(-1.06)	(-1.81)
Brown	0.007	-0.002
	(1.00)	(-0.25)
Post	0.004	-0.002
	(0.45)	(-0.21)
Green*Post	-0.012	0.002
	(-0.76)	(0.19)
Brown*Post	-0.012	-0.001
	(-0.83)	(-0.15)
Size	0.002	0.002
	(1.07)	(0.98)
Loss	-0.001	0.002
	(-0.09)	(0.33)
Quick	0.002	0.001
	(0.31)	(0.11)
Leverage	-0.011	-0.012*
	(-1.30)	(-1.85)
ROA	-0.005	-0.006
	(-0.81)	(-1.05)
Momentum	-0.011	0.004
	(-1.30)	(1.26)
Mtb	-0.002	-0.003
	(-0.95)	(-0.99)
N	42,746	82,600
Industry fixed effect	Y	Y
Time fixed effect	Y	Y
$AdjR^2$	0.002	0.002

Table 11: **Alternative Measurement: Trading Volume**

This table uses retail investor trading volume as an alternative measurement. Volume is calculated as the total buy and sell of a firm per day divided by the total volume per month. Results hold consistent with the main result.

Volume	Post = 7 days		Post = 14 days
	(1)	(2)	(3)
Green	-0.001	-0.003**	-0.001
	(-0.61)	(-2.12)	(-1.63)
Brown	0.001	0.001	0.001
	(0.64)	(0.37)	(0.71)
Post		0.001	0.000
		(0.52)	(0.73)
Green*Post		0.005**	0.002
		(2.22)	(1.61)
Brown*Post		-0.004	0.003
		(-0.09)	(0.23)
Size	-0.002***	-0.002***	-0.001***
	(-3.42)	(-3.42)	(-3.65)
Leverage	0.001	0.001	0.002
	(0.90)	(0.89)	(0.57)
ROA	0.005***	0.005***	0.003***
	(3.95)	(3.88)	(4.40)
Loss	-0.002*	-0.002*	-0.002***
	(-1.88)	(-1.86)	(-2.59)
Quick	-0.000*	-0.000	-0.000**
	(-1.52)	(-1.49)	(-2.19)
Momentum	-0.002***	-0.002***	-0.002***
	(-2.83)	(-2.82)	(-3.10)
mtb	-0.000***	-0.000**	-0.000***
	(-2.67)	(-2.48)	(-3.09)
N	29,394	29,394	53,691
Industry fixed effect	Y	Y	Y
Time fixed effect	Y	Y	Y
$Adj R^2$	0.405	0.405	0.672

Table 12: **Environmental, Social and Governance Dimension**

This table tests whether the net buying behaviour of retail investors in green firms originates from a particular dimension. I also test three subsamples, which means I test the relationship between OrderImbalance and Green*Post when E_high equals 1, or S_high equals 1, or G_high equals 1. Results hold consistent.

OrderImbalance(Mroibtrd)	Environmental Dimension	Social Dimension	Governance Dimension
	(1)	(2)	(3)
Green	0.018*	0.007	-0.001
	(1.71)	(0.76)	(-0.05)
Post	0.010	0.009	0.011
	(1.23)	(1.20)	(1.51)
Green*Post	-0.026***	-0.013	-0.016
	(-2.78)	(-1.35)	(-1.41)
E_high	0.011		
	(0.95)		
Green*E_high	-0.038***		
	(-2.88)		
Post*E_high	-0.030**		
	(-2.37)		
Green*Post*E_high	0.052***		
	(4.51)		
S_high		0.029***	
		(2.87)	
Green*S_high		-0.038***	
		(-4.92)	
Post*S_high		0.004	
		(0.22)	
Green*Post*S_high		0.003	
		(0.03)	
G_high			0.005
			(0.61)
Green*G_high			-0.003
			(-0.19)
Post*G_high			-0.199
			(-1.67)
Green*Post*G_high			0.028
			(1.36)
Controls	Yes	Yes	Yes
N	29,394	29,394	29,394
Industry fixed effect	Y	Y	Y
Time fixed effect	Y	Y	Y
Eventcounty fixed effect	Y	Y	Y
$Adj R^2$	0.004	0.004	0.003

Table 13: **Different Exogenous Shock: Covid-19**

Following the previous study (Dottling and Kim, 2022), I define the Covid-19 shock as the period between 21st-Feb-2020 and 25th- Apr-2020, and the pre-Covid period from 1st-jan-2020 to 20th-Feb-2020. Covid is omitted by weekly time fixed effect. The following result is comparable with their study. Under the economic crisis, retail investors net sell more on high ESG disclosure score firm after Covid-19.

$$OrderImbalance(Mroibtrd_{i,d}) = \alpha + \beta_1 Green_{i,t} * Covid + \beta_2 Covid + \beta_3 Green_{i,t} + \beta_4 Brown_{i,t} + \beta_5 Brown_{i,t} * Covid + \beta_6 X_{i,t} + FixedEffect + \epsilon_{it}$$

OrderImbalance(Mroibtrd)	(1)
Green	0.033***
	(2.89)
Brown	-0.310***
	(-6.22)
Green*Covid	-0.016**
	(-2.19)
Brown*Covid	0.073
	(0.82)
Size	0.003
	(0.20)
Leverage	-0.025***
	(-3.25)
ROA	-0.033***
	(-5.18)
Loss	-0.026**
	(-2.23)
Quick	0.001
	(0.39)
Momentum	-0.011**
	(-2.07)
Mtb	0.001***
	(3.10)
N	14,042
Industry fixed effect	Y
Time fixed effect	Y
$AdjR^2$	0.008

9. Appendix

9.1. Variable Definition

Variable	Definition
Dependent Variables	
Order Imbalance (Mroibtrd)	The difference between the number of marketable retail buy trades and the number of marketable retail sell trades divided by the number of retail buy trades plus the number of retail sell trades
Trading Volume	The total number of retail buy trades plus retail sell trades
Independent Variables	
Green	Green is a dummy variable, which equals to one if firms are under high ESG disclosure score in Bloomberg, and zero otherwise; High ESG disclosure score is defined by the uppermost quintile across the year-industry level
Brown	Brown is a dummy variable, which equals to one if firms are under low ESG disclosure score in Bloomberg, and zero otherwise; low ESG disclosure score is defined by the lowest quintile across the year-industry level
Post	Post is a time variable, which equals to one if firms' subsidiary experience the extreme weather event that cause more than 1 billion direct damage, and zero otherwise
Logdaycnt	Logdaycnt is firm i's natural log of one plus the number of days with any extreme weather events in fiscal year t
Logdaycntpast	Logdaycntpast is firm i's natural log of one plus the average number of days with any extreme weather events in fiscal years t-3, t-2, and t-1 from NOAA database
Logabdaycnt	Logabdaycnt is the residual value from the annual regression of Logdaycnt on Logdaycntpast in fiscal year t

Appendix 9.1 (continued)	
Dowell	Dowell is a dummy variable, which equals to one if its cash flow is higher than the mean value of its industry at the quarter level
Other Control Variables	
Size	The size of the company, measured as the natural logarithm of laggard assets
Leverage	Leverage, measured by short term and long-term debt divided by book value of equity
Loss	Loss is a dummy variable, which equals to one if net income is negative and zero otherwise
ROA	Return on asset, measured by firm's net income divided by total asset
Mtb	Market to book ratio, measured by firm's market value divided by firm's book value
Momentum	Momentum is based on the performance of each stock over the preceding 12 months, and stocks are categorized into different momentum groups based on their cumulative returns during this period. Stocks with ranks in the rank 70 to 100 are assigned a momentum value of -1; Stocks with ranks in 0 to 30 are assigned a momentum value of 1; Stocks with ranks between rank 30 and 70 are assigned a momentum value of 0
HighPresence	High_presence is a dummy variable, which equals to one if a firm generates more tweets than the average number of tweets of its industry
HighExpo	High_expo is a dummy variable, which equals to one if the average number of weather-related words in the annual report exceeds the sample mean average in the annual report

9.2. Extreme Weather Event from 2010 to 2020 in the U.S. - Classified by County and direct damage

No	No of types	Hazard	Date	County	State
1	#1	Flooding	01-May-10	Davidson	TN
2	#2	Hail	06-Oct-10	Maricopa	AZ
3	#3	Tornado	27-Apr-11	Limestone	AL
4				Tuscaloosa	AL
5	#4	Tornado	22-May-11	Jasper	MO
6	#5	Hail	13-Jun-12	Dallas	TX
7	#6	Wind	29-Oct-12	Monmouth	NJ
8				Ocean	NJ
9	#7	Tornado	20-May-13	Cleveland	OK
10	#8	Tornado	17-Nov-13	Tazewell	IL
11	#9	Flooding	11-Aug-14	Wayne	MI
12	#10	Flooding	25-Oct-15	Navarro	TX
13	#11	Hail	04-Apr-16	Bexar	TX
14	#12	Flooding	12-Aug-16	Ascension	LA
15				East Baton Rouge	LA
16				Lafayette	LA
17				Livingston	LA
18				Tangipahoa	LA
19	#13	Hurricane/Tropical Storm	08-Oct-16	St. Johns	FL
20	#14	Hail	08-May-17	Jefferson	CO
21	#15	Hurricane/Tropical Storm	25-Aug-17	Aransas	TX
22				Nueces	TX
23		Flooding	25-Aug-17	Brazoria	TX
24				Fort Bend	TX
25				Galveston	TX
26				Harris	TX

Appendix 9.2 (continued)					
27				Jefferson	TX
28				Liberty	TX
29				Montgomery	TX
30				Orange	TX
31	#16	Flooding	21-Sep-17	Adjuntas	PR
32				Barceloneta	PR
33				Toa baja	PR
34	#17	Wildfire	05-Sep-18	Shasta	CA
35	#18	Hurricane/Tropical Storm	12-Sep-18	New Hanover	NC
36	#19	Wildfire	07-Oct-18	Tehama	CA
37	#20	Wildfire	06-Nov-18	Los Angeles	CA
38	#21	Wildfire	08-Nov-18	Butte	CA
39	#22	Tornado	20-Oct-19	Dallas	TX
40	#23	Tornado	02-Mar-20	Davidson	TN
41	#24	Hurricane/Tropical Storm	27-Aug-20	Calcasieu	LA
42				Orange	TX

All the events output from SHELDUS database including affected state and county. If there are several events that happen in the same day, I keep the one that cause larger damage.
I then manually check the latitude and longitude of the extreme weather event location preparing for testing the impact on affected firms. For the location of affected firms, I get the city and states of firms' headquarter from Compustat. Compustat has county variable, but most observations are missed. Therefore, I match the city and state of firms' headquarter with their counties by using data provided by the US census, which helps me to get the latitude and longitude of firms' county location as well. If one hazard hit different counties, it will under the same No of types.

References

Alessandrini, F., Baptista Balula, D. and Jondeau, E. (2021), 'ESG Screening in the Fixed-Income Universe', *Swiss Finance Institute Research Paper* pp. 21–77.
URL: $https://papers.ssrn.com/sol3/papers.cfm?abstract_id = 3966312$

Anderson, A. and Robinson, D. T. (2019), 'Climate fears and the demand for green investment', *Swedish House of Finance Research Paper* (19-14).

Angeles Lopez-Cabarcos, M., M Perez-Pico, A. and Lopez Perez, M. L. (2020), 'Investor sentiment in the theoretical field of behavioural finance', *Economic Research-Ekonomska Istraživanja* **33**(1), 2101–2228.

Ardia, D., Bluteau, K., Boudt, K. and Inghelbrecht, K. (2020), 'Climate change concerns and the performance of green versus brown stocks', *National Bank of Belgium, Working Paper Research* (395).

ASU Center for Emergency Management and Homeland Security (2022), 'The Spatial Hazard Events and Losses Database for the United States, Version 20.0 [Online Database]. Phoenix, AZ: Arizona State University.'.
URL: *Available from https://cemhs.asu.edu/sheldus*

Avramov, D., Cheng, S. and Tarelli, A. (2022), 'Active Fund Management when ESG Matters: An Equilibrium Perspective', *Available at SSRN 4182602* .

Baldauf, M., Garlappi, L. and Yannelis, C. (2020), 'Does climate change affect real estate prices? Only if you believe in it', *The Review of Financial Studies* **33**(3), 1256–1295.

Barber, B. M., Huang, X., Odean, T. and Schwarz, C. (2021), 'Attention induced trading and returns: Evidence from robinhood users', *Journal of Finance, forthcoming* .

Barber, B. M. and Odean, T. (2008), 'All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors', *The Review of Financial Studies* **21**(2), 785–818.

Barrot, J.-N. and Sauvagnat, J. (2016), 'Input specificity and the propagation of idiosyncratic shocks in production networks', *The Quarterly Journal of Economics* **131**(3), 1543–1592.

Bassi, A., Colacito, R. and Fulghieri, P. (2013), ''O sole mio: An experimental analysis of weather and risk attitudes in financial decisions', *The Review of Financial Studies* **26**(7), 1824–1852.

Behrendt, S., Finance, A. S. J. o. B. . and 2018, u. (2018), 'The Twitter myth revisited: Intraday investor sentiment, Twitter activity and individual-level stock return volatility', *Journal of Banking & Finance* **96**, 355–367.
URL: *https://www.sciencedirect.com/science/article/pii/S0378426618302115*

Bergmann, A., Stechemesser, K. and Guenther, E. (2016), 'Natural resource dependence theory: Impacts of extreme weather events on organizations', *Journal of Business Research* **69**(4), 1361–1366.

Boehmer, E., Jones, C. M., Zhang, X. and Zhang, X. (2021), 'Tracking retail investor activity', *The Journal of Finance* **76**(5), 2249–2305.

Bolton, P. and Kacperczyk, M. (2021), 'Do investors care about carbon risk?', *Journal of Financial Economics* **142**(2), 517–549.

Bourveau, T. and Law, K. K. F. (2021), 'Do disruptive life events affect how analysts assess risk? Evidence from deadly hurricanes'.

Brown, J. R., Gustafson, M. T., Ivanov, I. T., Almeida, H., Berlin, M., Carey, M., Cortes, K. R., James, C., Johnson, K., Lewellen, S., Meisenzahl, R., Mihov, A., Nichols, J., Ranish, B., Sarama, R., Schoar, A. and Seru, A. (2021), 'Weathering cash flow shocks', *Wiley Online Library* **LXXVI**(4), 1731–1772.
URL: *https://onlinelibrary.wiley.com/doi/abs/10.1111/jofi.13024*

Ceccarelli, M., Ramelli, S. and Wagner, A. F. (2021), 'Low-carbon mutual funds', *Swiss Finance Institute Research Paper* (19-13).

Cheng, F., Chiao, C., Wang, C., Fang, Z. and Yao, S. (2021), 'Does retail investor attention improve stock liquidity? A dynamic perspective', *Economic Modelling* **94**, 170–183.

Chevalier, J. and Ellison, G. (1999), 'Are some mutual fund managers better than others? Cross-sectional patterns in behavior and performance', *The Journal of Finance* **54**(3), 875–899.

Choi, D., Gao, Z. and Jiang, W. (2020), 'Attention to global warming', *The Review of Financial Studies* **33**(3), 1112–1145.

Choi, J.-H., Kim, C., Kim, J.-B. and Zang, Y. (2010), 'Audit office size, audit quality, and audit pricing', *Auditing: A Journal of practice & theory* **29**(1), 73–97.

Chomsky, N. and Pollin, R. (2020), *Climate crisis and the global green new deal: The political economy of saving the planet*, Verso Books.

Chui, A. C. W., Subrahmanyam, A. and Titman, S. (2022), 'Momentum, reversals, and investor clientele', *Review of Finance* **26**(2), 217–255.

Coval, J. and Stafford, E. (2007), 'Asset fire sales (and purchases) in equity markets', *Journal of Financial Economics* **86**(2), 479–512.

Dale, V. H., Efroymson, R. A. and Kline, K. L. (2011), 'The land use–climate change–energy nexus', *Landscape Ecology* **26**(6), 755–773.

De Lucia, C., Pazienza, P. and Bartlett, M. (2020), 'Does good ESG lead to better financial performances by firms? Machine learning and logistic regression models of public enterprises in Europe', *Sustainability* **12**(13), 5317.

Dehaan, E., Madsen, J. and Piotroski, J. D. (2017), 'Do weather-induced moods affect the processing of earnings news?', *Journal of Accounting Research* **55**(3), 509–550.

Dessaint, O., Foucault, T., Frésard, L. and Matray, A. (2016), 'Ripple effects of noise on corporate investment'.
URL: $https://papers.ssrn.com/sol3/papers.cfm?abstract_id = 2726561$

Ding, R. and Hou, W. (2015), 'Retail investor attention and stock liquidity', *Journal of International Financial Markets, Institutions and Money* **37**, 12–26.

Dottling, R. and Kim, S. (2022), 'Sustainability preferences under stress: evidence from COVID-19', *Journal of Financial and Quantitative Analysis* pp. 1–39.

Eaton, G., Green, C., Roseman, B., Wu, Y. and Eaton, W. (2021), 'Zero-commission individual investors, high frequency traders, and stock market quality', *High Frequency Traders, and*

Stock Market Quality .

URL: *https://microstructure.exchange/slides/RobinhoodSlides$_T$ME.pdf*

Eccles, R. G., Serafeim, G. and Krzus, M. P. (2011), 'Market interest in nonfinancial information', *Journal of Applied Corporate Finance* **23**(4), 113–127.

Edmans, A. (2022), The End of ESG.

URL: *https://papers.ssrn.com/sol3/papers.cfm?abstract$_i$d* = 4221990

Engle, R. F., Giglio, S., Kelly, B., Lee, H. and Stroebel, J. (2020), 'Hedging climate change news', *The Review of Financial Studies* **33**(3), 1184–1216.

Erhemjamts, O., Huang, K. and Tehranian, H. (2022), 'Climate Risk, ESG Performance, and ESG Sentiment for US Commercial Banks'.

Fang, L. and Peress, J. (2009), 'Media coverage and the cross-section of stock returns', *Journal of Finance* **64**(5), 2023–2052.

Finta, M. A. (2022), 'Retail Investors' Activity and Climate Disasters', *Available at SSRN* .

Furukawa, K., Ichiue, H. and Shiraki, N. (2020), How Does Climate Change Interact with the Financial System? A Survey How Does Climate Change Interact with the Financial System? A Survey , Technical report, Bank of Japan.

Gabzdylova, B., Raffensperger, J. F. and Castka, P. (2009), 'Sustainability in the New Zealand wine industry: drivers, stakeholders and practices', *Journal of cleaner production* **17**(11), 992–998.

Gall, M., Borden, K. A. and Cutter, S. L. (2009), 'When do losses count? Six fallacies of natural hazards loss data', *Bulletin of the American Meteorological Society* **90**(6), 799–810.

Gall, M., Borden, K. A., Emrich, C. T. and Cutter, S. L. (2011), 'The unsustainable trend of natural hazard losses in the United States', *Sustainability* **3**(11), 2157–2181.

Gantchev, N., Giannetti, M. and Li, R. (2021), 'Sustainability or performance? Ratings and fund managers' incentives', *Ratings and Fund Managers' Incentives (November 19, 2021). Swedish House of Finance Research Paper* (21-4).

Gholami and Sands, J. (2022), ‘Environmental, Social and Governance Disclosure and Value Generation: Is the Financial Industry Different?’, *Sustainability* **14**(5), 2647.
URL: *https://www.mdpi.com/2071-1050/14/5/2647*

Ghosh, P. and Zhang, J. (2021), ‘Do Investors Hedge Climate Risk? Evidence from 19 Million Retail Stock Traders’, *Evidence from* **19**.

Gisa (2018), ‘General Insurance Statistical Agency Agence statistique d’assurance générale’.

Goldstein, I., Kopytov, A., Shen, L. and Xiang, H. (2022), On ESG investing: Heterogeneous preferences, information, and asset prices, Technical report.

Greenough, G., McGeehin, M., Bernard, S. M., Trtanj, J., Riad, J. and Engelberg, D. (2001), ‘The potential impacts of climate variability and change on health impacts of extreme weather events in the United States.’, *Environmental Health Perspectives* **109**(suppl 2), 191–198.

Guimaraes, P. and Portugal, P. (2010), ‘A simple feasible procedure to fit models with high-dimensional fixed effects’, *The Stata Journal* **10**(4), 628–649.

Hadley, S. W., Erickson III, D. J., Hernandez, J. L., Broniak, C. T. and Blasing, T. J. (2006), ‘Responses of energy use to climate change: A climate modeling study’, *Geophysical research letters* **33**(17).

Hamid, A. and Heiden, M. (2015), ‘Forecasting volatility with empirical similarity and Google Trends’, *Journal of Economic Behavior & Organisation* **117**, 62–82.
URL: *https://www.sciencedirect.com/science/article/pii/S0167268115001687*

Han, Y., Mao, C. X., Tan, H. and Zhang, C. (2020), ‘Distracted Analysts: Evidence from Climatic Disasters’, *Fox School of Business Research Paper Forthcoming* .

Hartzmark, S. M. and Sussman, A. B. (2019), ‘Do investors value sustainability? A natural experiment examining ranking and fund flows’, *The Journal of Finance* **74**(6), 2789–2837.

Heidari, N. and Pearce, J. M. (2016), ‘A review of greenhouse gas emission liabilities as the value of renewable energy for mitigating lawsuits for climate change related damages’, *Renewable and sustainable energy reviews* **55**, 899–908.

Hirshleifer, D. A., Myers, J. N., Myers, L. A. and Teoh, S. H. (2008), 'Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades', *The Accounting Review* **83**(6), 1521–1550.

Hu, Z. (2022), 'Social interactions and households' flood insurance decisions', *Journal of Financial Economics* **144**(2), 414–432.

Huang, H. H., Kerstein, J. and Wang, C. (2018), 'The impact of climate risk on firm performance and financing choices: An international comparison', *Journal of International Business Studies* **49**(5), 633–656.

Johnson, A. C., Acreman, M. C., Dunbar, M. J., Feist, S. W., Giacomello, A. M., Gozlan, R. E., Hinsley, S. A., Ibbotson, A. T., Jarvie, H. P. and Jones, J. I. (2009), 'The British river of the future: how climate change and human activity might affect two contrasting river ecosystems in England', *Science of the Total Environment* **407**(17), 4787–4798.

Kaiser, L. (2020), 'ESG integration: value, growth and momentum', *Journal of Asset Management* **21**(1), 32–51.

Kelkar, U. and Bhadwal, S. (2007), 'South Asian regional study on climate change impacts and adaptation: implications for human development', *Human development report* **2008**, 47.

Klibanoff, P., Lamont, O. and Wizman, T. A. (1998), 'Investor reaction to salient news in closed-end country funds', *The Journal of Finance* **53**(2), 673–699.

Kong, D., Lin, Z., Wang, Y. and Xiang, J. (2021), 'Natural disasters and analysts' earnings forecasts', *Journal of Corporate Finance* **66**, 101860.

Krueger, P., Sautner, Z. and Starks, L. T. (2020), 'The importance of climate risks for institutional investors', *The Review of Financial Studies* **33**(3), 1067–1111.

Larrain, B., Tapia, M. and Urzua, F. (2017), 'Investor protection and corporate control', *Journal of Corporate Finance* **47**, 174–190.

Latino, C., Pelizzon, L. and Rzeźnik, A. (2021), 'The power of ESG ratings on stock markets'.

Li, Q., Watts, E. M. and Zhu, C. (2023), 'Retail investors and ESG news', *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper* .

Lins, K. V., Roth, L., Servaes, H. and Tamayo, A. (2022), 'Sexism, culture, and firm value: Evidence from the Harvey Weinstein scandal and the# MeToo movement', *University of Alberta School of Business Research Paper* (2019-509).

Martin, P. R. and Moser, D. V. (2016), 'Managers' green investment disclosures and investors' reaction', *Journal of Accounting and Economics* **61**(1), 239–254.

Moss, A., Naughton, J. P. and Wang, C. (2020), 'The irrelevance of ESG disclosure to retail investors: Evidence from Robinhood', *Available at SSRN 3604847* .

Mottola, G., Valdes, O., Ganem, R., Fontes, A. and Lush, M. (2022), 'Investors Say They Can Change the World, If They Only Knew How: Six Things to Know About ESG and Retail Investors', *FINRA Investor Education Foundation* pp. 1–13.

Mysiak, J., Torresan, S., Bosello, F., Mistry, M., Amadio, M., Marzi, S., Furlan, E. and Sperotto, A. (2018), 'Climate risk index for Italy', *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* **376**(2121), 20170305.

Nagar, V. and Schoenfeld, J. (2022), 'Measuring weather exposure with annual reports', *Review of Accounting Studies* pp. 1–32.

Naveed, M., Sohail, M. K. and Naqvi, Z. (2020), 'Role of ESG Disclosure in Determining Asset Allocation Decision: An Individual Investor Perspective'.
URL: *https://www.researchgate.net/publication/343290566*

Noy, I. (2017), 'To leave or not to leave? Climate change, exit, and voice on a Pacific Island', *CESifo Economic Studies* **63**(4), 403–420.

Ozik, G., Sadka, R. and Shen, S. (2021), 'Flattening the illiquidity curve: Retail trading during the COVID-19 lockdown', *Journal of Financial and Quantitative Analysis* **56**(7), 2356–2388.

Oztamur, D., sciences, K. P.-S., behavioral and 2014 (2014), 'Exploring the role of social media for SMEs: as a new marketing strategy tool for the firm performance perspective', *Procedia-Social and behavioral sciences* **150**, 511–520.
URL: *https://www.sciencedirect.com/science/article/pii/S1877042814051167*

Pastor, L., Stambaugh, R. F. and Taylor, L. A. (2021), 'Sustainable investing in equilibrium', *Journal of Financial Economics* **142**(2), 550–571.

Peloza, J., Loock, M., Cerruti, J. and Muyot, M. (2012), 'Sustainability: How stakeholder perceptions differ from corporate reality', *California Management Review* **55**(1), 74–97.

Rakotomavo, M. T. J. (2011), 'Preferences of retail investors and institutions for corporate social performance', *Journal of Sustainable Finance & Investment* **1**(2), 93–102.

Ramos, S., Latoeiro, P. and Veiga, H. (2020), 'Limited attention, salience of information and stock market activity', *Economic Modelling* **87**, 92–108.
URL: *https://www.sciencedirect.com/science/article/pii/S0264999318311519*

Rao, R. K. S. and Bharadwaj, N. (2008), 'Marketing initiatives, expected cash flows, and shareholders' wealth', *Journal of Marketing* **72**(1), 16–26.

Rose, A. M. (2020), 'A Response to Calls for SEC-Mandated ESG Disclosure', *Wash. UL Rev.* **98**, 1821.

Sautner, Z. and Starks, L. T. (2021), 'ESG and Downside Risks: Implications for Pension Funds', *Wharton Pension Research Council Working Paper* (2021-10).

Seasholes, M. S. and Wu, G. (2007), 'Predictable behavior, profits, and attention', *Journal of Empirical Finance* **14**(5), 590–610.

Sippel, S., Walton, P. and Otto, F. E. L. (2015), 'Stakeholder perspectives on the attribution of extreme weather events: An explorative enquiry', *Weather, Climate, and Society* **7**(3), 224–237.

Taylor, J., Vithayathil, J. and Yim, D. (2018), 'Are corporate social responsibility (CSR) initiatives such as sustainable development and environmental policies value enhancing or window dressing?', *Corporate social responsibility and environmental management* **25**(5), 971–980.

Tetlock, P. C., Chan, W., Daniel, K., Glosten, L., Goyal, A., Huberman, G., Jones, C., Kelley, E., Lynch, A., Parsons, C., Pasquariello, P., Saar, G., Seasholes, M., Spiegel, M., Subrahmanyam, A. and Tookes, H. (2010), 'Does public financial news resolve asymmetric information?', *The Review of Financial Studies* **23**(9), 3520–3557.
URL: *https://academic.oup.com/rfs/article-abstract/23/9/3520/1671631*

Vujanovic, A. and Gallagher, M. (2017), 'Psychological Impact of Natural Disasters in Adults'.
URL: *https://www.uh.edu/class/news/archive/2017/august-september/natural-disasters-impact-adults/*

Wang, B., Long, W. and Wei, X. (2018), 'Investor attention, market liquidity and stock return: a new perspective', *Asian Economic and Financial Review* **8**(3), 341–352.

Wong, W. C., Batten, J. A., Mohamed-Arshad, S. B., Nordin, S. and Adzis, A. A. (2021), 'Does ESG certification add firm value?', *Finance Research Letters* **39**, 101593.

Xie, J., Nozawa, W., Yagi, M., Fujii, H. and Managi, S. (2019), 'Do environmental, social, and governance activities improve corporate financial performance?', *Business Strategy and the Environment* **28**(2), 286–300.

Yu, E. P.-y. and Van Luu, B. (2021), 'International variations in ESG disclosure–do cross-listed companies care more?', *International Review of Financial Analysis* **75**, 101731.

Yung, K. and Nafar, N. (2017), 'Investor attention and the expected returns of reits', *International Review of Economics & Finance* **48**, 423–439.
URL: *https://www.sciencedirect.com/science/article/pii/S1059056016303707*

Zumente, I. and Bistrova, J. (2021), 'ESG importance for long-term shareholder value creation: Literature vs. practice', *Journal of Open Innovation: Technology, Market, and Complexity* **7**(2), 127.