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Marinela Adriana FINTA

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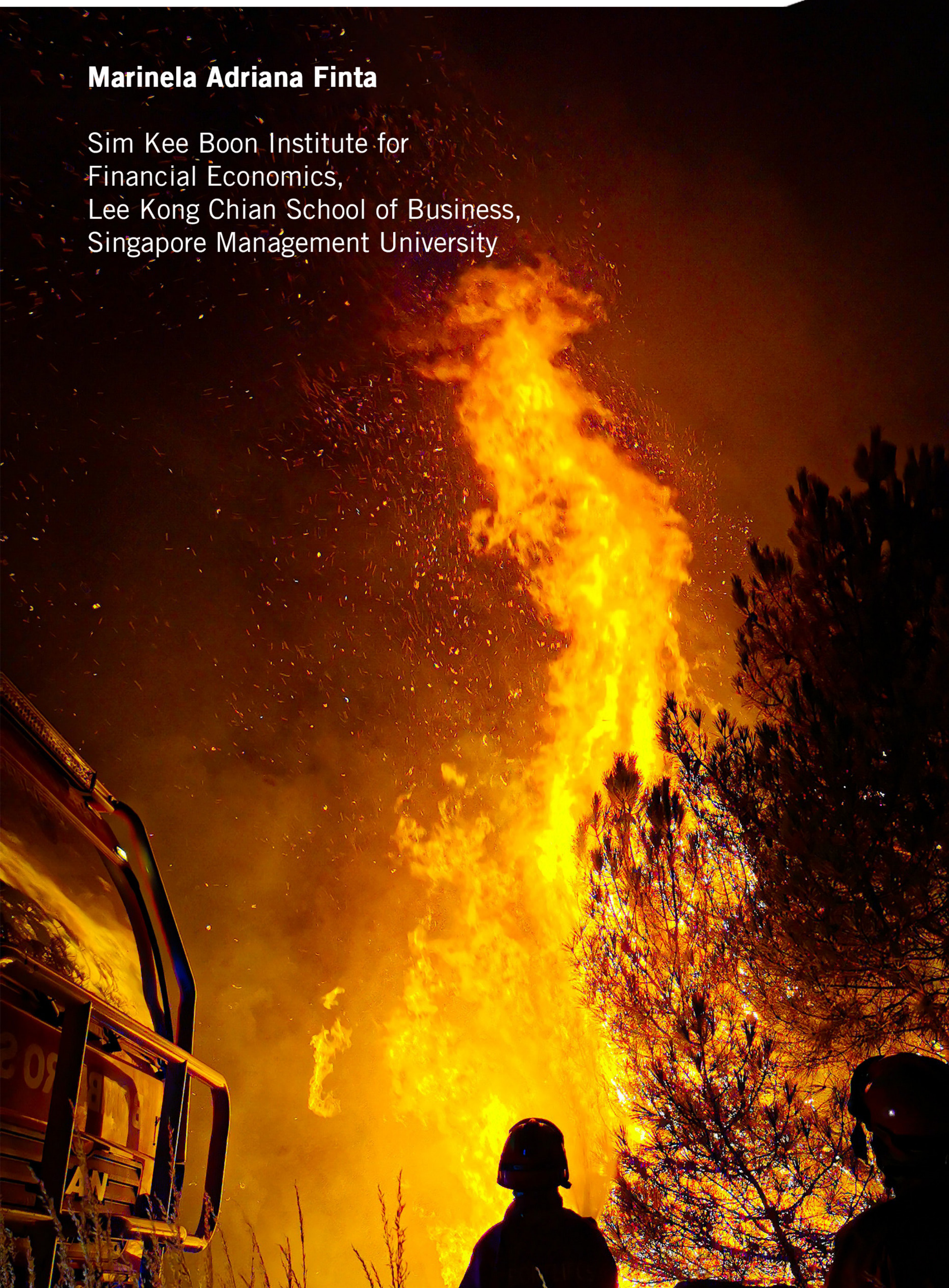
SIM KEE BOON INSTITUTE FOR FINANCIAL ECONOMICS

Marinela Adriana Finta

Sim Kee Boon Institute for Financial Economics,
Lee Kong Chian School of Business,
Singapore Management University



LEE KONG CHIAN SCHOOL OF BUSINESS

Retail Investors' Activity and Climate Disasters †

Marinela Adriana Finta*

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*Corresponding Author: Sim Kee Boon Institute for Financial Economics, Lee Kong Chian School of Business, Singapore Management University, 50 Stamford Road, 178899 Singapore; Emails: mfinta@smu.edu.sg, marinela.finta@gmail.com.

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Retail Investors' Activity and Climate Disasters

Abstract

We analyze the effects of climate disasters on retail investors' trading activity. Results show that retail investors trade significantly less during and around climate disasters, and retail buyers exhibit higher returns than sellers. Climate disasters weaken the positive return predictability of the past month's order imbalances while strengthening it for the past six month's order imbalances. In the short run, firms within climate disaster counties with retail net buying underperform those with negative imbalances. Instead, in the long run, firms within and outside climate disaster counties with positive order flows outperform those with negative order flows. Finally, the estimates on the return and order imbalance comovement around climate disasters are consistent with the main findings.

JEL Codes: G11, G12, G14, G41, Q54.

Keywords: Retail Investors; Climate Disasters.

1 Introduction

Understanding investors' trading behavior matters especially given the frequent occurrence of climate disasters and the extensive damage these cause. According to Adam Smith, the NOAA (National Oceanic and Atmospheric Administration) applied climatologist and economist, "Climate change is intensifying many of these extremes that lead to billion-dollar disasters." The former Director of the United Nations Office for Disaster Risk Reduction, Ricardo Mena, also reasserts, "There is a very sharp increase in the number of climate-related events, which are actually creating 77% of the total direct economic losses caused by disasters."[1] Indeed, recent studies find that these events adversely affect stock market returns and valuations, and not necessarily investors' or analysts' attention and proximity to them affect trading decisions. Their climate disaster experience (including early life), awareness, and emotion, instead, exert more influence and increase, e.g., risk aversion, regardless of their or a firm's exposure to them (Bernile et al., 2021; Alok et al., 2020; Bourdeau-Brien and Kryzanowski, 2020; Han et al., 2023).

Climate disasters, per se, precisely matter due to the salience (Bordalo et al., 2012) and emotional bias, i.e., "sensitivity to negative outcomes" these may carry (Clayton, 2020). As such, these events may induce investors to disregard some potentially relevant information and evaluate their effects and future probability of occurrence by "...the ease with which relevant instances come to mind" (Tversky and Kahneman, 1973; Bordalo et al., 2012). For instance, Alok et al. (2020) show that fund managers near a climate disaster underweight the disaster stocks relative to those located further away. Authors underline that it is not, in fact, the informational advantage, e.g., of being near the proximity of disaster or the superior information explaining their findings, but the salience bias. Thereby, as the study by Alok et al. (2020) already hints, "Retail investors may exhibit salience bias and overreact to the disasters by liquidating their investments in funds with greater investments in the disaster zone stocks." This is exactly the primary purpose of this study – investigating the role of climate disasters as an additional channel that can affect retail investors' trading activity and, in turn, their retail order imbalance influences returns.

[1] For more information, see CNN and AP (Associated Press) News. Moreover, as per NOAA and Forbes, 2023 has been the worst year for billion-dollar climate disasters, surpassing the 2017 historical and 2020 record years with 16 and 25 billion-dollar events.

While fund managers and institutional investors possess the necessary skills and strong ties with market players to interpret climate disasters accurately and are allocating large amounts of resources for a firm's analysis, retail investors might hold neither the skills nor resources. As a result, the effects of climate disasters on the informativeness of their trading decisions are particularly relevant as they may act as both noise traders and informed investors, impacting stock market prices. On the one side, they are more likely to overreact to and misinterpret these events. In particular, although the typical assumption would be that investors decide which firms to trade by considering all available information, this is not always true. According to the above salience and emotional story, retail investors' awareness of climate disasters and their consequences may emotionally impact trading decisions, leading them to focus too much on these disasters and presumably omitting other relevant information. In line with Bordalo et al.'s (2012) theoretical model, we posit that since retail investors are "...made keenly aware of the consequences of" climate disasters, they may overreact to them by being more likely to make mistakes and act as noise traders. Thus, we expect a negative relationship between their trades and future returns.

On the other side, such salient climate disasters may provide retail investors with an informational advantage so that their trades positively predict future stock returns. As such, retail investors may also act as informed traders. According to this hypothesis, since climate disasters are highly prominent along with their effects, retail investors could be skillful at gathering information about them if they, e.g., think disasters contain helpful and superior information for their trading decisions. Using the retail trades executed on NYSE from 2004 to 2011, Akbas and Subasi (2019) show that retail investors benefit more from corporate news during times of high market and firm-specific uncertainty and that these events significantly increase the predictive ability of retail volume for future stock returns (Barrot et al., 2016). Moreover, Kelley and Tetlock (2013) underline that "...retail traders have clear incentives to trade on novel information gleaned from geographic proximity to firms, relationships with employees, or insights into customer tastes...." Hence, climate disasters may provide insights into their stock pricing role, but it is essential to highlight that we do not expect them to benefit from these events.[2] As such, the central question is – Do retail investors

[2]As climate disasters would typically increase the visibility of firms with exposure to them, investors would be less willing to buy stocks in such firms. Naturally, if some retail investors can correctly interpret climate disasters, then to reduce losses, they could sell their shares in such disaster firms. Nevertheless, even if that is the case, in line with Akbas and Subasi (2019), who examine the negative news, "...their effect would be limited since they are

overreact to climate disasters? If so, do climate disasters lead to an information disadvantage on the future performance of stock prices and, thus, a less profitable trading strategy during them? Or, can retail investors accurately assess the implications of climate disasters for their trading decisions and evaluation of the earnings surprises?

This paper assesses the impacts of climate disasters on retail investors' trading activity and their role on stock pricing and firms' fundamentals from January 2010 to December 2018. Using climate disasters as exogenous shocks enables us to provide new insights into the informativeness of retail investors' decisions and analyze their trading on firms *with* and *without* exposure to these events, i.e., the climate disaster (CD) and non-CD firms. In doing so, it follows the novel approach of Boehmer et al. (2021), relying on publicly available U.S. equity transaction data to identify marketable retail purchases and sales. Authors define retail investors as sellers if the transaction prices are just above a round penny and buyers if they are just below a round penny. In addition, it uses unique and hand-collected climate disaster information, such as the exact dates of the occurrence of major disasters, i.e., those with damages above $1 billion. Hence, it accounts that certain events may last fewer or more days, making the available monthly occurrence dates irrelevant.

By using daily retail investors' activity measures such as the total trading volume, buy and sell volume, the order imbalances (i.e., the difference between buys and sells divided by the sum of buys and sells), and climate disasters, our paper is the first to provide answers to the following questions. Do climate disasters affect the trading behavior of retail investors? If yes, does their trading around them display certain returns? What is the role of retail investors in stock pricing during climate disasters? Are retail investors more likely to make mistakes in their trading decisions during disasters? Or can they correctly predict future returns during these events? What about their role in correctly predicting news about firms' fundamentals? If retail investors have new information about a firm's cash flows, their imbalances, would predict the earnings surprises (i.e., the proxy for firms' fundamentals) correctly. Lastly, can retail traders' trading induce a comovement in returns and own order imbalances around climate disasters?

Our main findings highlight climate disasters' influence on retail investors' trading activity and, hence, their trades' predictive ability for future returns. First, investors trade less on climate disas-

outnumbered by other individual investors who might trade in mixed directions for various reasons."

ter days and are usually net sellers during and around them, e.g., the average buy and sell volume, and total trading volume is significantly lower on climate disaster versus other days. Moreover, there is around a 30% decrease in investors' trading within climate disaster counties versus those outside them, indicating that retail investors overreact to disasters. Consistent with this idea, while in the week after climate disasters, we find average negative returns for the CD firms with both net sellers and buyers, one month after them, their returns are significantly positive for firms with i) buyers and sellers and ii) those with net buyers.[3] In addition, retail buyers exhibit higher returns than sellers around climate disasters (e.g., one and six weeks before and after them). Second, we find that retail order flows are less persistent during disasters and, in line with Kelley and Tetlock (2013) and Boehmer et al. (2021), positively predict earnings surprises and future returns in the short and long run.

Our results also contribute to the ongoing debate on retail investors' role towards future returns by proposing a new and additional channel, climate disasters, which can affect the informativeness of their decisions. Specifically, our analysis shows that these events negatively influence stock returns by reducing the short-term informativeness of retail investors. For instance, during these events, the past one-month order imbalances negatively predict next week's returns, whereas the past six-month imbalances positively predict next week's returns. While the former findings are more consistent with the noise trader hypothesis and retail investors' trading in the wrong direction by making mistakes systematically (Barber and Odean, 2008; Barber et al., 2009), the latter are in line with the information story according to which they are informed and, thus, trade in the right direction (Boehmer et al., 2021; Barrot et al., 2016; Kaniel et al., 2012; Kaniel et al., 2008; Chordia and Subrahmanyam, 2004).[4]

Third, we document a short-run underperformance of firms' positive retail order imbalances within climate disaster counties over firms with negative order imbalances, suggesting that, on average, retail investors cannot choose the right stocks to buy and sell. In other words, they do not appear to have an informational advantage, at least in the short run, in selecting stocks exposed to climate

[3] This evidence also signals that retail investors do not trade less on climate disaster firms because they might have access to superior information concerning the future performance of these firms. If that were the case, we would expect a decrease in their performance following such events. Instead, CD firms earn high returns in the long run.

[4] If local bias hypothetically drives our results, retail trades would be informative about future stock prices rather than our finding of short-run overreaction and mistakes in retail investors' trading activity.

disasters. This empirical evidence, instead, is more consistent with Bordalo et al.'s (2012) theoretical framework, implying, in our case, that the awareness and emotional impact that climate disasters convey also affect retail investors, leading them to act more like noise traders.[5] In contrast, in the long run, we note an overperformance of firms' positive retail order imbalances within and outside climate disaster counties over those with negative imbalances, which suggests that investors trade in the right direction. Finally, the average return and order imbalances' comovement results align with previous ones. That is, firms within and outside climate disaster counties experience a reduction in comovement from the low to the high order imbalance portfolio. Also, as we expect, the comovement estimates are more substantial between firms within climate disaster counties and disaster portfolios than the non-disaster portfolios. The non-CD firms, instead, comove more with the non-CD and CD portfolios when retail investors are net sellers and buyers, respectively.

The remainder of the paper is organized as follows. Sections 2 and 3 point out the related literature and data, respectively. In Section 4, we discuss our empirical findings. Finally, Section 5 concludes the paper.

2 Related Literature

Our paper relates to various streams of literature. It first contributes to the literature on retail investors and their implications for asset pricing. Despite many studies looking into retail investors' activity, the conclusions concerning what drives their trading or informativeness and, thus, effects on future stock returns are still controversial. On the one hand, individual investors are thought of as unsophisticated or "noise" traders (Barber et al., 2008) who are also subject to behavioral biases such as overconfidence (Barber and Odean, 2000, 2001), attention, e.g., they are net buyers of attention-grabbing stocks (Barber and Odean, 2008), and sensation-seeking (Barber et al., 2009). Such uninformed investors are likely to trade randomly (i.e., buy or sell stocks) and overtrade, consequently earning lower future returns and incurring substantial losses. We add to this literature by showing that climate disasters influence retail investors' trading activity. In particular, it drives investors to trade suboptimally and most likely make trading mistakes, especially when purchasing

[5] The findings of statistically insignificant returns for the non-CD portfolios in the short run around climate disasters also reassert this framework.

or selling stocks experiencing a climate disaster.

Moreover, Barber et al. (2023) recently point out that attention-induced buying can also explain the finding of retail order imbalance negatively predicting short-term returns in stocks with unusually high retail volume. Specifically, the authors argue that a large share of retail purchases is on attention-grabbing stocks, which underperform and, thus, diminish the overall returns. We extend the study of Barber et al. (2023) by documenting that retail order imbalance negatively predicts short-run returns for stocks with exposure to climate disasters. As the retail trading volume is substantially low during these disasters, attention-driven bias cannot explain our findings, which we assert are consistent with the noise trader theory.

On the other hand, recent studies view retail investors as informed traders who can correctly predict future stock returns and trade accordingly (Kaniel et al., 2008; Kaniel et al., 2012; Kelley and Tetlock, 2013; Barrot et al., 2016; Boehmer et al., 2021). Aside from acting as uninformed and informed investors, retail traders can also act as liquidity providers, i.e., supply liquidity to institutional investors' immediate demand (Kaniel et al., 2008; Kaniel et al., 2012). As possible explanations to reconcile the earlier literature, Kelley and Tetlock (2013) postulate that retail investors' skills might i) vary across brokerages and ii) have also improved over time. As such, their trades positively predict future returns and earnings surprises. Individual investors are likewise informed about earnings announcements; e.g., Kaniel et al. (2012) show this is due to holding private information or being skillful at processing public information and their role as liquidity providers. Boehmer et al. (2021) find that the persistence and liquidity provision of retail order flows account for around half of the positive predictive power of order imbalance for future returns, and the remainder reflects informed trading. The aggregate retail order imbalance's predictive ability for future returns also intensifies in periods of market stress, i.e., high uncertainty (Barrot et al., 2016; Akbas and Subasi, 2019). Our study advances the above works by providing new insights into another channel, namely, climate disasters, affecting retail investors' trading and informativeness.

Second, our paper relates to the literature on the impacts of climate disasters on firms and capital markets. Exposure to climate disasters leads to inferior stock market valuations (Seetharam,

2017) and supply disruptions, which, in turn, translate into a reduction in operating performance (Pankratz and Schiller, 2023), sales growth, and equity value losses (Barrot and Sauvagnat, 2016). For instance, Seetharam (2017) shows that U.S. companies with exposure to climate disasters exhibit between 0.3% to 0.7% lower returns than those without exposure to such events. Climate disasters also depress the current prices of the firms' stocks and bonds, which leads to negative contemporaneous and higher future returns (Huynh and Xia, 2023). These findings, thus, suggest the investors' overreaction to them.

Third, by looking into retail investors, our paper adds to the literature on the effects of climate disasters on managers' and institutional investors' decisions. Recent research shows that climate disaster experiences of individuals and investors have long-lasting effects on their risk-taking behavior and decision-making (Bernile et al., 2017; Bernile et al., 2021; Bharath and Cho, 2023; Han et al., 2023). For instance, Bernile et al. (2017) show that even such early life experiences make the chief executive officers (CEOs) more risk-averse, taking more conservative corporate policies (i.e., lower leverage and higher cash holdings) and financing decisions (i.e., less debt to cover the financing deficit). Individuals are also more risk-averse and have lower future return expectations. Bharath and Cho (2023) document disasters' long-lasting effects on the household's future portfolio decisions even after moving to an area less prone to them, e.g., "...disaster effect shows up, on average, more than 6 years after the move and is visible for up to 24 years after the move." Disasters further distract analysts' attention, who issue less accurate earnings forecasts (Han et al., 2023). Likewise, fund managers become more risk-averse, reducing their portfolio's volatility after personally experiencing a disaster, even though such events do not affect their holdings (Bernile et al., 2021).

Other studies highlight that even knowledge of such disasters influences investors' decisions through their salience and the emotional bias like stress and anxiety these convey (Dessaint and Matray, 2017; Bourdeau-Brien and Kryzanowski, 2020; Berry-Stoelzle et al., 2023). As Loewenstein et al.'s (2001) risk-as-feelings theory postulates, "Responses to risky situations (including decision making) result in part from direct emotional influences...", i.e., emotions that "...often produce behavioral responses that depart from what individuals view as the best course of action." Therefore, by e.g., viewing images of climate disasters or people suffering in the media, investors may ignore part of essential information, focusing on "...what comes to their mind" (Tversky and Kahneman, 1973; Bordalo et al., 2012). According to Tversky and Kahneman (1973), "Continued preoccupation with an outcome may increase its availability, and hence its perceived likelihood. Consequently, availability provides a mechanism by which occurrences of extreme utility (or disutility) may appear more likely than they actually are." Dessaint and Matray (2017), for example, document an overreaction of managers who, by solely being aware of neighborhood hurricanes, temporarily increase corporate cash holdings. Disaster salience influences insurers who invest more in climate risk management (Berry-Stoelzle et al., 2023) and increases bond market investors' risk aversion due to emotional bias (Bourdeau-Brien and Kryzanowski, 2020).

Furthermore, institutional investors also believe climate risks are essential, affecting their portfolio risk and returns (Krueger et al., 2020). In a recent study by Alok et al. (2020), mutual fund managers overreact to climate disasters by disinvesting from firms experiencing climate disasters mainly due to the salience bias.[6] That is, "...the tendency to overweight probabilities based on the ease with which events can be recalled" (Tversky and Kahneman, 1973). These results support Bordalo et al.'s (2012) theoretical model of choice under risk in which investors are risk averse towards and overweight the payoffs of the salient downside events. Specifically, in their model, "local thinkers", i.e., "...decision makers do not take into account fully all the information available to them, but overemphasize the information their minds focus on."

On the whole, our paper draws on the above literature and hypothesizes that climate disasters could influence retail investors' trading activity. In particular, they may overestimate the risk of salient climate disasters not necessarily because of proximity (i.e., their local bias) but simply by being aware of such events' intensity and emotional impact (Tversky and Kahneman 1973). Therefore, in our setting, we expect climate disasters, as exogenous shocks, to receive much media and policymakers' attention due to their extensive damage and, as such, to influence the informativeness of retail investors' decisions.

[6] They also confirm that neither behavioral biases nor preferences to reduce exposure to local disaster zone stocks of their retail investors create flow-driven trading pressure. To do so, they do not look at retail trades but consider the local population's socioeconomic characteristics (e.g., age, income, unemployment, race) at the disaster county as a proxy for their client/investor base.

3 Data

We use the TAQ trade data and approach of Boehmer et al. (2021) to identify the U.S. retail investor activity from January 2010 to December 2018. Specifically, we include the common stocks with shares codes 10 and 11 and classify trades as retail purchases (sales) if prices are just below (above) the round penny. We then merge these retail measures with the CRSP and Compustat's stock returns and accounting data. The analysts' earnings forecasts are from Institutional Brokers Estimate System (I/B/E/S).

Table 1 presents the summary statistics of retail order imbalances and buy and sell volume. Specifically, we calculate the daily time-series statistic, i.e., mean, median, standard deviation, skewness, kurtosis, and percentile values for each retail measure and stock in our sample, and then take the cross-sectional mean. The mean retail order imbalance is negative, i.e., -0.04, with a standard deviation of 0.47, suggesting that investors sell more than buying. Indeed, note that the average sell volume is greater than the buy volume. Overall, although we include a more extended sample period, the statistics align with Boehmer et al. (2021).

INSERT TABLE 1 HERE

We collect the monthly climate disaster aggregated data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). This database covers a wide range of natural hazards such as thunderstorms, hurricanes, floods, wildfire, and tornados and perils such as flash floods and heavy rainfall. However, solely focusing on monthly data to assess investors' activity may not be relevant as climate disasters may occur at the beginning or middle of the month and last more or fewer days. To address these possible issues, relying on the month when a climate disaster occurs from SHELDUS and Google search engine, we manually look for and collect the exact start days of all the major climate disasters, i.e., those with damages above $1 billion.

Table 2 presents the major climate disasters, i.e., drought, flooding, hail, hurricane/tropical storm, tornado, wildfire, wind, and winter weather, covering the period from January 2010 to December 2018. We report the event intensity, breadth of impact, and frequency of occurrence, i.e., the average events and damages in $ billions, the U.S. counties and states affected by them, and the number of firms in those counties. Among these events, flood is the most relevant disaster, with the largest damage of $73.78 billion, affecting most states, counties, and firms. Hail and tornados are the following significant disasters entailing $10.60 and $8.62 billion in damages, respectively, but occur less frequently and affect fewer states and counties. Wildfire cause similar damages to previous events, $8.52 billion, yet these are less likely to occur, e.g., we include four events that affect one state and four counties. Instead, hurricanes/tropical storms rank close to the median in terms of damage, frequency, and the number of affected counties. Finally, the last three climate disasters in wide-scale damage of around $2.75 billion and above $1 billion are the droughts and wind and winter weather events, respectively. Regarding frequency and impact, extreme wind events occupy the second rank after floods, followed by tornadoes, hurricanes, and hail.

INSERT TABLE 2 HERE

4 Empirical Findings

This section discusses the empirical findings using daily measures of retail investors' activity. In our primary analyses, to reduce the microstructure noise, we follow the study of Boehmer et al. (2021) in using overlapping daily frequency data for the weekly order imbalance and return measures. We define the days with climate disasters as the days when these events occur for the first time, and to control for the possibility of a delay between the actual announcement of the disaster in the news and its occurrence, we also include the day before and after the announcement. If the disasters last longer than a day, we consider those days too as being climate disaster days. Hence, over the entire paper, when referring to climate disasters, we also account for their duration.

We start our analysis by exploring whether climate disasters influence the daily retail investors' activity, such as order imbalances and buy and sell volume, in Section 4.1. We then assess the relationship between order imbalances and short and long-run returns around climate events in Section 4.2. In Sections 4.3, 4.4, and 4.5, we examine the determinants of order imbalances during climate disasters and whether the past retail investors' order flows can i) predict future returns and earning surprises and ii) provide relevant information to construct a trading strategy during climate disasters. The last sections, i.e., Sections 4.6 and 4.7, investigate if retail investors' trading around climate disasters can lead to comovement in returns and order imbalances.

4.1 *Do climate disasters affect retail investors' trading?*

We start our empirical analysis by exploring whether climate disasters influence retail investors' trading. That is, Table 3 addresses whether investors' trading varies on climate versus non-climate disasters days, whereas Table 4 looks into their trading solely during climate disaster days and hence, their trading behavior towards firms from counties with or without climate disasters. In addition, Table 5 presents retail investors' activity around these events.

Table 3 shows whether the average retail investors' trading activity, i.e., order imbalances, buy and sell volume, and their difference are significantly different during climate and non-climate disaster days. Specifically, we calculate the time-series average for each retail measure and stock during climate and non-climate disaster days and then take the cross-sectional mean. We find that retail order imbalances are more significantly negative during climate than non-climate disaster days, e.g., -0.036 versus -0.031, suggesting an increasing retail selling during disasters. However, their cross-sectional mean difference is not statistically significant. The retail buy and sell volume and the total trading volume, i.e., the sum of the buy and sell volume, generally confirm the previous findings. Moreover, the difference between climate disaster and non-disaster days is statistically significant for both buy and sell volume and the total trading volume emphasizing that investors trade less on disaster days, which substantially matter. In Appendix A.1, we further confirm this decline in retail investors' trading activity by considering the mean retail measures of firms from inside and outside the state where a climate disaster occurs.[7]

INSERT TABLE 3 HERE

We next consider the retail investors' behavior by solely exploring climate disaster days. Specifically, Table 4 presents the time-series averages of cross-sectional means for our retail measures on climate disaster days when considering the firms with headquarters in a county that is affected versus non-affected by a disaster, i.e., the CD and non-CD firms. The findings are consistent with those of

[7] In particular, Panels A and B of Appendix A.1 report the significant cross-sectional averages of retail trading activity for firms in the same state (excluding the firms from climate disaster counties) and outside the state of disaster events, respectively, on climate versus non-climate disaster days. It also reports their significant retail buy, sell, and total trading volume means difference.

Table 3 emphasizing the retail investors' overreaction to climate disasters. In particular, during such days, they trade significantly less, e.g., around 30%, in firms with than without exposure to disasters. For instance, the significant mean difference between the total trading volume of CD and non-CD firms is around −29000, and the buy and sell volume is usually around half of it.[8]

INSERT TABLE 4 HERE

Table 5 explores retail investors' trading activity one week before to after climate disasters. Considering CD firms, it reports the time-series averages of the cross-sectional mean for the order imbalances, buy and sell volume, and total volume. In particular, for each CD firm, we compute the cross-sectional averages of retail measures and then take the time-series means for every day during the one week before to after the event. Instead, since climate disasters may last more days, for the disaster period (i.e., 0), we compute the cross-sectional average of the time-series means (e.g., we take i) the mean for each event and CD firm, ii) average across the events for each firm and iii) the cross-sectional mean).

Investigating Table 5 shows that order imbalances are significantly more negative during disasters than in the prior week, whereas these are less negative afterward. These results suggest that, usually, on average, retail investors are substantial net sellers during and after the climate disasters. Indeed, total trading volume reduces, especially from two days before the event, reaching its lowest level during the disaster period. Afterward, it remains low for the entire week. We note similar patterns for the retail buy and sell volume, which, akin to trading volume, significantly decreases around and especially during climate disasters. Once again, our findings highlight the retail investors' relatively low trading (i.e., buying and selling) during and in the short run around climate disasters. Appendix A.3 confirms Table 5's results by showing the statistically significant mean differences in buy and sell volume and total trading volume one month before and after climate disasters. This significance also holds for including order imbalances three months before and after the disaster events. In line with Table 5 and Appendix A.3, Appendix A.4 reports the averages of retail investors' activity around climate disasters and their differences, but when considering the non-CD

[8]Similar to Appendix A.1, Appendix A.2 reports the significant time-series averages of cross-sectional means for retail measures of firms inside and outside the disaster state. The results confirm that on climate disaster days, there is a statistically significant lower trading volume, i.e., total, buy, and sell volume, for CD than non-CD firms when considering the state rather than the county.

firms, i.e., those from counties without climate disasters. Similar to previous results, non-CD firms display a relatively low trading volume during and in the week after disasters. Interestingly, their magnitude and average differences between one month before and after disasters are usually similar to those in Appendix A.3. The total trading volume difference in Appendices A.3 and A.4 is 6,479 versus 5,797, respectively, i.e., around 10% between the CD and non-CD firms. Moreover, even the difference between three months before and after disasters is only 17.5% smaller than that in Appendix A.3. This suggests that even long after disasters, retail investors continue to trade less in CD and non-CD firms, yet their trading resumes more in the non-CD firms.[9]

INSERT TABLE 5 HERE

4.2 *Does retail investors' trading around climate disasters display certain returns?*

Our analyses so far show that climate disasters affect the behavior of retail investors. Accordingly, the next question is whether there exists a relationship between retail investors' trading activity around climate disasters and returns. In other words, do low, medium, or high retail order imbalances exhibit various return trends around climate disasters? To answer this question, we sort the firms within the climate disaster counties into terciles using the retail order imbalances and report the short and long-run returns and order imbalances in Panels A and B, respectively, of Tables 6 and 7. The former and latter tables report the average percentage returns and retail order imbalances one week and six weeks before and after climate disasters for firms affected by them, respectively.

Examining Table 6, we typically observe positive returns one week before and during the climate disasters for medium and high retail order imbalances portfolios within the climate disaster counties. Yet, these are usually statistically significant only for the medium portfolio before climate disasters. Instead, when retail investors sell more than buy, the low portfolio's returns are negative and significantly small one day and week before climate disasters except during them. After the climate disasters, we remark negatively significant average returns for the low, medium, and high order

[9]As robustness, Appendix A.5 presents the average retail investors' trading activity one week before to after each climate disaster (i.e., drought, flooding, hail, hurricane, tornado, wildfire, wind, and winter weather) for the CD firms. Generally, retail trading volume decreases during each event when it hits the lowest values and maintains its level also the following week. The winter weather, tornado, wind, and hurricane disasters exhibit the lowest trading volume among our events.

imbalances portfolios. These findings indicate that usually around climate disasters, in the short-run, retail investors are better off when buying and selling and when they are net buyers rather than sellers.

INSERT TABLE 6 HERE

In the long run, i.e., six weeks before and after the climate disasters, Table 7 strengthens Table's 6 results by documenting the significantly positive returns of both high and medium order imbalances portfolio, especially four and six weeks after them. Moreover, the low portfolio exhibits significant negative returns, mainly during the first three weeks after disasters, highlighting the potential drawbacks of retail investors when they are net sellers rather than buyers. Taken together, the average negative returns in the short run and positive in the long run, e.g., starting from the second week after climate disasters, reconfirm again retail investors' trading overreaction due to climate disasters.

INSERT TABLE 7 HERE

4.3 *What explains retail investors' order imbalances during climate disasters?*

The previous results emphasize that climate disasters affect retail investors' activity. Moreover, Boehmer et al. (2021) show that past returns and order imbalances explain the future retail investors' order flows. Given the above, Table 8 reports the determinants of retail investors' order flows during climate disasters by adopting the Fama and MacBeth (1973) two-stage estimation where in the first stage, for each day, we estimate the following regression:

$$\begin{aligned} Oib(i,w) = {} & b_0 + b_1 * Event\,Dummy + b_2 * Oib(i,w-1) + b_3 * Oib(i,w-1) * Event\,Dummy \\ & + b_4 * Controls(i,w-1) + u_0(i,w) \end{aligned} \tag{1}$$

where the $Event\,Dummy$ is one during climate disasters and zero, otherwise, and $Oib(i,w)$ is the retail order imbalance measure for a firm i at week w (i.e., from day 1 to day 5). The $Oib(i,w-1)$ is the past order imbalance measure from day -4 to day 0. We also include the returns over the past week and month and the past six-month returns. As control variables, we consider the previous month's turnover, volatility of daily returns, size (i.e., the logarithm of market capitalization), and the logarithm of book-to-market (B/M). Relying on the above daily coefficients, in the second stage, we take their averages, and as Equation (1) uses overlapping daily frequency data, we adjust the standard errors using Newey-West (1987) with five lags.

The dummy coefficient, i.e., b_1 indicates that during a climate disaster, the one-week ahead order imbalances significantly increase by 0.0504. The negative b_3 coefficient suggests that the effect of past order imbalances on future order imbalances is 0.0527 lower during climate disasters than in non-climate disasters. As such, past order imbalances are significantly less persistent during climate disaster events. Specifically, during climate disasters, the average effect of past order imbalances on future order imbalances, namely, $b_2 + b_3$ is 0.0868 (i.e., 0.1395+(−0.0527)), whereas, when there are no climate disasters, it is 0.1395. In line with Boehmer et al. (2021), coefficients for the past week, month, and six months returns are highly significant, i.e., −0.7632, −0.2725, and −0.0411, indicating that over the above periods, retail investors are contrarian (i.e., buy losers and sell winners). The control variables' coefficients are significantly positive for the previous month's turnover, daily return volatility, and size and negative for the logarithm of book-to-market (B/M). Hence, retail investors tend to buy large, high volatility and turnover firms.

INSERT TABLE 8 HERE

4.4 *Predicting future stock returns and earnings surprises with retail order imbalances around climate disasters*

Can retail investors' order imbalances provide relevant information for i) cumulative abnormal returns (CAR) and ii) future short and long-term stock returns around climate disasters? What about concerning the earnings surprises? In this section, Tables 9, 10 and 11 provide the answers to these questions. Specifically, Table 9 first explores the predictability of cumulative abnormal returns around climate disasters (e.g., one week and month ahead as well as two and three months ahead) by estimating the following panel regression model:

$$CAR(i,w) = c_1 * Oib(i,w-1) + c_2 * Controls(i,w-1) + u_1(i,w) \tag{2}$$

where $CAR(i, w)$ is the cumulative abnormal returns for a firm i over w week/s ahead (e.g., one week [1, 5] - from day 1 to day 5, four weeks [1, 21] - from day 1 to day 21, and likewise for the two [1, 42] and three [1, 63] weeks ahead). We include the past week returns, firm, month and year fixed effects and akin control variables to Table 8. Our results show a significant positive relationship between the past week's order imbalances and future CAR (e.g., the prediction around climate disasters is 1.19, 1.53, and 2.17 basis points). That is, the one-, two-, and three-month CAR are significantly higher when retail investors buy more than sell in a given week before climate disasters.

INSERT TABLE 9 HERE

Second, Table 10 presents the short (i.e., one week ahead) and long-run (i.e., from two to twelve weeks ahead) return predictability of the retail order imbalances during climate disasters. Similarly to Table 8, we estimate Fama–MacBeth regressions as follows:

$$\begin{aligned} Ret(i,w) = {} & d_0 + d_1 * Event\,Dummy + d_2 * Oib(i,w-1) + d_3 * Oib(i,w-1) * Event\,Dummy \\ & + d_4 * Oib(i,m-1) + d_5 * Oib(i,m-1) * Event\,Dummy \\ & + d_6 * Oib(i,[m-7,m-2]) + d_7 * Oib(i,[m-7,m-2]) * Event\,Dummy \\ & + d_8 * Controls(i,w-1) + u_2(i,w) \end{aligned} \tag{3}$$

where the $Event\,Dummy$ is one during climate disasters and zero, otherwise, and $Ret(i, w)$ is the stock returns for a firm i over certain days of a week w and w weeks ahead (e.g., [1, 5] - from day 1 to day 5 and w=2 captures the two weeks ahead return rather than the cumulative return over the next two weeks). The $Oib(i, w-1)$ is the past order imbalance measure from day -4 to day 0. In addition, we consider the past month ($Oib(i, m-1)$) and six month $Oib(i, [m-7, m-2])$ order imbalance measures. We control for the past week and month returns, and the six month returns. The control variables are the same as those in Equation (1).

We find that during climate disasters, the one-week and six-month returns significantly decrease by -0.25% and -0.28%, respectively, whereas the other horizons' coefficients are statistically insignificant. Consistent with previous results, the past week and month order imbalances usually significantly and positively predict the returns in both the short and long run. Especially in the short-run, climate disasters significantly weaken the positive return predictability of the past month's order imbalances, strengthening it for the past six-month order imbalances. For example, the average effects of the past one and six months' order imbalances for one-week ahead returns are −0.13% (i.e., −0.0015+0.0002) and 0.04% (i.e., 0.0004+0.00001), respectively. Another method to evaluate climate disasters' relevance relies on the number of climate disaster days. That is, as 27.81% of the days in our sample period display climate disasters then one standard deviation increase in past one and six months' order imbalances leads to an overall performance of the next week returns of around −0.022% (i.e., 27.81% * −0.0013 + (1−27.18%) * 0.0002) and 0.012% (i.e., 27.81% * 0.0004 + (1−27.18%) * 0.00001), respectively. The positive relationship is consistent with Boehmer et al.'s (2021) information story, according to which retail investors' order imbalances are persistent (i.e., their' buying and selling pressure), and they are contrarian and informed about the stock price movements. Hence, their trading can positively predict the returns (Chordia and Subrahmanyam, 2004; Kaniel et al., 2008). In contrast, the negative relationship suggests that retail investors i) are "liquidity demanding" or "noise" traders trading at unfavorable prices due to rational investors requiring compensation or ii) may mistakenly trade in the wrong direction, due to emotional bias and salience that these disasters convey. Thus, when there are climate disasters, past one-month order imbalances negatively predict next week's returns.

Regarding our control variables, we note significantly negative coefficients on the previous one-week returns, especially for the next day to one-week ahead returns. In contrast, coefficients on the previous six-month returns are highly positive and significant. These positive and negative coefficients indicate return reversals and momentum in the short and long run, respectively. The past-one month returns, turnover, volatility, size, and B/M are usually statistically insignificant, reinforcing that return predictability is not due to these factors.[10]

INSERT TABLE 10 HERE

Finally, Table 11 investigates retail order imbalances' ability to predict the earnings surprises during climate disasters. Following Kelley and Tetlock (2013), as a proxy for the earnings surprises, we use the sign of analysts' earnings forecast errors, i.e., the difference between actual earnings-per-share

[10] Appendix A.6 shows that our results are also robust when estimating Equation (3) only with the past one-month order imbalances and the other control variables akin to Table 10.

and the median I/B/E/S analyst forecast, and estimate a logistic regression model as follows:

$$\begin{aligned} FE(i,[t+x,t+y]) = e_0 &+ e_1 * Event\,Dummy + e_2 * Oib(i,[0]) + e_3 * Oib(i,[0]) * Event\,Dummy \\ &+ e_4 * Ret(i,[0]) + e_5 * Ret(i,[-5,-1]) + e_6 * Ret(i,[-26,-6]) \\ &+ e_7 * Controls(i,w-1) + u_3(i,[t+x,t+y]) \end{aligned} \tag{4}$$

where the $Event\,Dummy$ is one during climate disasters and zero, otherwise, and $FE(i,[t+x,t+y])$ is the forecast error dummy equal to one when the earnings forecast errors over days $t+x$ and $t+y$ are positive and zero if there is a negative surprise for a firm i. The independent variables include the $Oib(i,[0])$ and $Ret(i,[0])$ are the daily order imbalance measure and returns of firm i for day 0. We also control for the past week ($Ret(i,[-5,-1])$) and month $Ret(i,[-26,-6])$ returns, and the past month's size and logarithm of the book-to-market. In line with Kelley and Tetlock (2013), we require at least fifty earnings announcements for each daily logistic regression.

The negatively significant event dummy coefficients indicate a climate disaster due change of 17.6% and 20.9% (e.g., $e^{-0.735-1}$ and $e^{-0.565-1}$) in the odds of a positive earnings surprise during days [1, 2] and [6, 20]. Consistent with Kelley and Tetlock (2013), order imbalances positively predict the earnings surprises during days [1, 2], [1, 3], and [1, 5]. Considering the one-week predictability, a bottom-to-top decile change in retail order imbalances yields a change of 45.8% (i.e., $e^{0.1547(0.685-(-0.735))-1}$) in the odds ratio for a positive earnings surprise. In addition, we show that order imbalances contain valuable information for short-term earnings surprises during climate disasters. For instance, these events significantly reduce the influence of order imbalances on the one-week ahead earnings surprises (i.e., $0.1547+(-0.3830)=-0.2283$). Thus, an average bottom-to-top decile change in order imbalances produces a change of 26.6% in the odds ratio for a positive earnings surprise.

INSERT TABLE 11 HERE

4.5 *Can we use retail investors' trading as a signal to create a trading strategy during climate disasters?*

Previous sections emphasize the importance of climate disasters for the informativeness of retail investors' decisions, indicating that they are more likely to overreact in the short run and make trading mistakes. Thereby the next question is whether, on days with climate disasters, there is a difference in retail investors' ability to choose stocks to buy and sell belonging to CD and non-CD firms. Is their selection likewise in the wrong direction, or is it not? If their choice is indeed in line with previous evidence – in the wrong direction, then firms with positive retail order imbalances would exhibit lower returns than those with negative imbalances. Otherwise, the former firms would outperform the latter ones. In this section, we sort firms into two groups to address this question using the previous week's retail order imbalance on each climate disaster day. Then for each group, we consider the CD and non-CD firms. Table 12 presents the short (next day to one week ahead) and long-run (two to twelve weeks ahead) portfolio returns and the long−short strategy returns consisting in buying the stocks with the highest order imbalance and selling stocks with the lowest order imbalance. Specifically, Panels A and B report the percentage value-weighted portfolio returns based on the previous month's market capitalization in both the short and long run.[11]

In the short run (e.g., [1, 3] and [1, 4] days ahead), Panel A documents significant negative high−low portfolio returns for the CD firms. These negative returns suggest that, indeed, retail investors trade in the wrong direction, i.e., on average, they cannot select the right stocks of firms from climate disaster counties to buy and sell. Moreover, even when buying more than selling stocks of firms outside disaster counties, investors experience negative returns, though insignificant, due to climate disasters. Similarly, it is worth underlining the mainly statistically insignificant returns of the CD and non-CD portfolios. These findings align with our hypothesis on the awareness of climate disasters triggering an emotional overreaction by investors, even though these effects mainly concern the CD firms. In Panel B, we observe significantly positive high−low portfolio returns for CD firms, especially over the eight-, ten-, and twelve-week horizons (e.g., 1.99%, 2.45%, and 2.43%), while for the non-CD firms, returns are statistically significant starting from the fourth week).[12] These results imply that when investors buy more than sell stocks of firms from or outside disaster counties, they achieve favorable long-term returns.[13]

[11] Note that as Boehmer et al. (2021) mention, this table ignores the trade frictions and transaction costs, and thus, it solely relies on retail order imbalances as a signal in predicting future stock returns.

[12] See also the short and long-run alphas from Appendix A.7, which confirm Table 12's conclusions about the sign of long−short portfolio returns. The statistical significance holds in short run for the CD firms and the long run for both CD and non-CD firms.

[13] Appendix A.8 reports the short-run, long-run, and long−short portfolio returns and their relationship with

INSERT TABLE 12 HERE

4.6 *Can retail investors' trading induce return comovement around climate disasters?*

This section discusses the return comovement estimates i) on the portfolio returns from Appendix A.8, and ii) on the CD and non-CD portfolio returns from Table 12, for CD and non-CD firms.

We start by discussing the return comovement estimates on the portfolio returns from Appendix A.8 for CD and non-CD firms. In particular, to obtain the coefficients, we estimate the rolling regression model of the below Equation (5) for each of the low, high, and high−low portfolios using a forward-looking 30-day window:

$$Ret(i,t) = f_0 + f_1 * Pf(t) + f_2 * Controls(t) + u_4(i,t) \tag{5}$$

where the $Ret(i,t)$ is the firm's i returns on day t, and Pf captures each of the low, high, and high−low portfolio returns. As control variables, we add the Fama and French (1993) three factors (see, e.g., Goetzmann et al., 2015). We then sort each of the f_1 daily comovement coefficients by the CD and non-CD firms and report their averages. Table 13 shows the value- and equal-weighted low, high, and high−low comovement coefficients (i.e., using the previous month's market capitalization) for the CD and non-CD firms in Panels A and B, respectively. Specifically, it informs us about the sensitivity of the CD and non-CD firms' returns to the order imbalance portfolio returns, i.e., whether their return comovement depends on retail investors being net sellers or buyers.

Results show a gradually positive and significant decline in the average return comovement from the low to the high portfolio for both CD and non-CD firms. The results confirm and reinforce once again our previous findings. For instance, during climate disasters, i) returns decline (see, e.g., Table 10), ii) investors are generally more net sellers than buyers in the short term (see, e.g.,

climate disasters. Similar to Table 12, the long-short strategy consists of buying stocks with the highest previous week's order imbalance and selling stocks with the previous week's lowest order imbalance regardless of whether in a climate disaster county. In particular, Panels A and B report significantly positive long−short portfolio returns in the short and long run, respectively. Panels C and D report the short- and long-run average estimates when regressing the low, high, and high-low portfolio returns on a climate dummy, one during days with climate disasters and zero otherwise. In line with Table 12, results show significantly negative returns for both low and high portfolios in the long run (e.g., over four to twelve weeks ahead). Moreover, the long-short portfolio return is also highly positive and significant over the eight, ten, and twelve weeks ahead. Thus, climate disasters lead to a greater decline in the short than long portfolio returns.

Tables 3 and 5), and iii) around disasters, when retail investors are net sellers their returns are negative (see, Table 6). Thus, given the above and retail investors' trading in the wrong direction in the short run, it makes sense that when retail investors are net buyers (i.e., high order imbalance) and sellers (i.e., low order imbalance) during climate disasters, to observe less and, respectively, more return comovement. In other words, during climate disasters, a CD and non-CD firm's return comoves less with the high order imbalance portfolio return and more with that of the low imbalance portfolio.[14]

INSERT TABLE 13 HERE

We next consider in more detail the return comovement estimates on the CD and non-CD portfolio returns from Table 12 for CD and non-CD firms. That is, we estimate the rolling regression model of the following Equations (6) and (7) for each CD and non-CD low, high, and high−low portfolio using a forward-looking 30-day window:

$$Ret(i,t) = g_0 + g_1 * Pf^{CD}(t) + g_2 * Controls(t) + u_5(i,t) \tag{6}$$

$$Ret(i,t) = h_0 + h_1 * Pf^{non-CD}(t) + h_2 * Controls(t) + u_6(i,t) \tag{7}$$

where the $Ret(i,t)$ is the firm's i returns on day t, and Pf^{CD} and Pf^{non-CD} capture each of the low, high, and high−low portfolio returns for firms affected and non-affected by a climate disaster, respectively. The control variables are those from Equation (5). Subsequently, we select from the above daily comovement coefficients those of the CD and non-CD firms and present their average and difference. Table 14 shows the CD and non-CD value- and equal-weighted low, high, and high−low comovement coefficients for the CD and non-CD firms in Panels A and B, respectively. In particular, this table looks at the sensitivity of the CD and non-CD firms' returns concerning the CD and non-CD order imbalance portfolio returns, namely, whether their return comovement relates to that of the portfolio returns relying on CD and non-CD firms where retail investors are net sellers and buyers.

In general, the CD firms' returns largely comove with the CD portfolio returns, regardless of whether the retail investors are net buyers or sellers. However, those of non-CD firms comove

[14] Appendix A.9 usually confirms Table's 13 results when using a forward-looking 90-day window.

more with the non-CD and CD portfolio returns when they are net sellers and buyers, respectively. In addition, considering the CD firms in Panel B, the difference in average return comovement coefficients between the CD and non-CD portfolio returns is statistically significant. That is, the returns of firms affected by a climate disaster display a higher return comovement with the climate disaster portfolio return (i.e., the average firms' returns within climate disaster counties) than with the non-CD portfolio return (i.e., the average firms' returns from outside climate disaster counties). Conversely, for the non-CD firms, the difference is usually statistically insignificant in both Panels A and B, e.g., the return comovement coefficients are mostly alike for the CD and non-CD portfolio returns. Our previous results hold for both the low and high portfolio returns, whereas those of the high−low portfolio returns are generally insignificant with negative comovement coefficients. The above findings indicate to some extent that the return comovement of CD and non-CD firms relates to that of the order imbalance portfolios, namely, retail investors' net purchases and sales.[15]

INSERT TABLE 14 HERE

4.7 *Can retail investors' trading lead to own order imbalance comovement around climate disasters?*

In this section, we further explore the order imbalance comovement akin to the return comovement of Tables 13 and 14.[16] To do so, using a forward-looking 30-day window, we estimate the following rolling regression models:

$$Oib(i,w) = m_0 + m_1 * Pf_{oib}(w) + u_7(i,w) \tag{8}$$

$$Oib(i,w) = p_0 + p_1 * Pf^{CD}_{oib}(w) + u_8(i,w) \tag{9}$$

$$Oib(i,w) = s_0 + s_1 * Pf^{non-CD}_{oib}(w) + u_9(i,w) \tag{10}$$

[15] Appendix A.10, most times aligns with Table's 14 findings when using a forward-looking 90-day window. We also find consistent results when using daily overlapping frequency for weekly returns. These results are available on request.

[16] Appendices A.11 and A.12 generally align with these tables' findings and sometimes even showing a greater significance when using a forward-looking 90-day window. We use the daily overlapping frequency of weekly order imbalances to account for the microstructure noise in order imbalances and for the fact that the CD and non-CD portfolio returns from Table 12 rely on the previous week's order imbalances.

where the $Oib(i,w)$ is the firm's i order imbalance measure, and Pf_{oib} captures each of the low, high, and high−low portfolio order imbalances. The Pf_{oib}^{CD} and Pf_{oib}^{non-CD} capture each of the low, high, and high−low portfolio order imbalances for firms affected and non-affected by a climate disaster, respectively. Afterward, we sort each of the daily order imbalance comovement coefficients from Equation (8) and Equations (9) and (10) by the CD and non-CD firms. Table 15 reports the average value- and equal-weighted low, high, and high−low order imbalance comovement coefficients for the CD and non-CD firms. Table 16 presents the CD and non-CD value- and equal-weighted low, high, and high−low order imbalance comovement coefficients for the CD and non-CD firms.

In Table 15, we remark that both CD and non-CD firms' order imbalances comovement follow close trends to the return comovement from Table 13. The high−low comovement coefficient is negatively significant for non-CD firms, but when using the forward-looking 90-day window in Appendix A.11, it is also significant for the CD firms. Regardless of the disaster county, firms' order imbalances comove more (less) with the low (high) order imbalance portfolio. These findings are plausible since, as Tables 3 and 5 highlight, retail investors are rather net sellers than buyers in the short term around climate disasters.

INSERT TABLE 15 HERE

Investigating Table 16, we typically observe the akin large comovement of the CD firms' order imbalances with the CD low and high order imbalance portfolios as in the case of returns. The order imbalance comovement of non-CD firms also depends on the retail investors' trading activity, e.g., more (less) prominent with the CD (non-CD) portfolio for net sellers (buyers). Instead, the difference between the CD and non-CD comovement coefficients is mainly insignificant for either CD or non-CD portfolios. Along the same line as the return comovement, CD and non-CD firms' order imbalance comovement often is statistically insignificant when considering either of the firms' high−low order imbalance portfolios. These results confirm the order imbalances' persistence and highlight the important role of comovement in retail investors' trades around climate disasters.

INSERT TABLE 16 HERE

5 Conclusion

In this paper, we investigate the U.S. retail investors' trading activity during climate disasters using the subpenny trade prices approach of Boehmer et al. (2021). Authors demonstrate that transactions occurring at prices just above a round penny are retail purchases, whereas those just below a round penny are retail sales.

Our results show that climate disasters considerably affect retail investors. They trade significantly less during and around disasters and are usually net sellers (i.e., on average, sell more than buy). We note that in the short term, the week before and during climate disasters, retail investors who either buy and sell or are net buyers experience positively significant returns, yet their portfolio returns are substantially negative afterward. In the long term, i.e., six weeks before and after the climate disasters, retail net buyers exhibit higher returns than net sellers. We next document that retail order imbalances are less persistent during climate events and can predict the cross-section of future stock returns and earnings surprises. In particular, climate disasters weaken the positive return predictability of the past month's order imbalances while strengthening it for the past six month's order imbalances. Disasters also diminish the effects of order imbalances on the one-week ahead earnings surprises.

Further, in the short run, firms within climate disaster counties with more positive retail order imbalances underperform those with more negative retail order imbalances. Instead, in the long run, firms within and outside climate disaster counties with more positive order flows outperform those with more negative order flows. Finally, in line with empirical findings, we observe a decline in the average return comovement from the low to the high order imbalance portfolio for firms within and outside climate disaster counties. The comovement is also substantial between firms' returns from disaster counties and the climate disaster portfolio return where retail investors are either net buyers or sellers. However, firms' returns outside the disaster counties comove more with the disaster and non-disaster portfolio return of retail net buyers and sellers, respectively. The order imbalance comovement presents similar patterns to the return comovement.

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Table 1: Summary Statistics

	Mean	Median	StdDev	Skewness	Kurtosis	Percentile 5th	25th	75th	95th
Order imbalances	−0.04	−0.05	0.47	0.01	2.64	−0.74	−0.42	0.35	0.69
Buy volume	38141	22901	60797	8.65	142	6974	13445	41169	112619
Sell volume	38207	23668	59009	8.93	148	7722	14246	41393	110069

Note: This table presents summary statistics of retail order imbalances, buy and sell volume, covering the period from January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021), and the order imbalance measure is defined as the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume. We calculate the time-series statistic (i.e., mean, median, standard deviation, skewness, kurtosis, and percentile values) for each retail measure and stock in our sample and then take the cross-sectional mean of it.

Table 2: Description of Climate Disasters

Disaster	Number of events	Total damages ($ billions)	County	State	Number of firms
Drought	10	2.754	10	2	135
Flooding	908	73.777	256	46	2240
Hail	50	10.598	37	17	379
Hurricane/Tropical Storm	88	4.484	62	10	507
Tornado	127	8.624	114	29	603
Wildfire	4	8.515	4	1	131
Wind	132	1.242	132	21	1158
Winter Weather	35	1.093	35	8	172

Note: This table presents the climate disaster events from January 2010 to December 2018. For each of our eight climate disasters, i.e., drought, flooding, hail, hurricane/tropical storm, tornado, wildfire, wind, and winter weather, we report the average number of events, the average damages in $ billions, the counties and states that have been affected by them and the number of firms in those counties.

Table 3: Retail Investors' Activity during Climate and Non-Climate Disaster Days

	Climate disaster	Non-climate disaster	Difference
Order imbalances	−0.036	−0.031	−0.005
	−6.08	−33.36	−0.93
Buy volume	33739	36854	−3115
	13.40	13.35	−2.23
Sell volume	33502	36793	−3291
	13.64	13.64	−2.45
Total volume	67242	73647	−6406
	13.56	13.50	−2.37

Note: This table presents the cross-sectional averages of the time-series means for retail investors' trading activity, i.e., order imbalances, buy and sell volume, and their difference, during climate and non-climate disaster days. In particular, we calculate the time-series average for each retail measure during climate and non-climate disaster days for each stock in our sample and then take the cross-sectional mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Table 4: Retail Investors' Activity during Climate Disasters

	CD	Non-CD	Difference
Order imbalances	−0.031	−0.034	0.004
	−2.94	−16.61	0.34
Buy volume	29019	43682	−14663
	12.96	49.77	−6.21
Sell volume	29470	43974	−14505
	12.69	49.92	−6.12
Total volume	58489	87657	−29167
	12.88	50.20	−6.19

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy and sell volume, and their difference, during climate disaster days for firms affected (CD) and non-affected (non-CD) by them. In particular, we calculate the cross-sectional mean for each retail measure during climate disaster days for CD and non-CD firms in our sample and then take the time-series mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Table 5: Retail Investors' Activity around Climate Disasters

	[−5, −1]	[−4, −1]	[−3, −1]	[−2, −1]	[−1]	0	[1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]
Order imbalances	−0.029	−0.029	−0.029	−0.033	−0.040	−0.035	−0.018	−0.027	−0.026	−0.025	−0.025
	−9.05	−6.97	−4.93	−4.80	−4.70	−5.91	−2.11	−2.96	−4.61	−6.43	−7.99
Buy volume	36392	36405	36839	35458	36045	33519	34486	34579	34355	35486	35818
	42.93	33.27	25.92	60.48	12.15	14.36	13.32	373.69	149.70	31.08	37.90
Sell volume	36118	36351	36335	35048	35357	33329	33746	34001	34390	35311	35496
	48.26	39.58	27.98	113.42	12.99	14.61	14.73	133.41	82.62	36.51	46.00
Total volume	72510	72756	73173	70507	71402	66849	68232	68579	68745	70797	71314
	47.02	37.01	26.94	78.76	12.62	14.53	14.12	197.41	263.95	34.37	42.51

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy and sell volume, one week before to after climate disasters for firms affected by them. We calculate the cross-sectional mean for each retail measure around climate disaster days in our sample and then take the time-series mean. Instead, for the climate disaster days (i.e., 0), we present the cross-sectional average of the time-series means for retail investors' trading activity. Specifically, as certain events may last more days, we take the mean for each event and CD firm in our sample, then average across the events for each firm, and finally, the cross-sectional mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Table 6: Short-Run Returns around Climate Disasters

	[−5, −1]	[−4, −1]	[−3, −1]	[−2, −1]	[−1]	0	[1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]
Panel A: Returns											
Low	−0.175	−0.109	−0.058	−0.025	−0.153	0.214	−0.185	−0.223	−0.319	−0.361	−0.326
	−1.98	−1.43	−0.72	−0.20	−1.84	5.09	−1.92	−5.99	−3.24	−4.43	−4.53
Medium	0.103	0.187	0.205	0.335	0.372	0.253	−0.370	−0.369	−0.290	−0.297	−0.207
	0.92	1.97	1.55	9.28	1.79	5.63	−4.24	−436.05	−3.69	−5.30	−2.06
High	−0.035	0.122	0.140	0.183	−0.008	0.237	−0.204	−0.110	−0.121	−0.170	−0.097
	−0.21	1.43	1.18	0.96	−0.10	4.33	−2.50	−1.16	−2.18	−2.72	−1.11
Panel B: Order imbalances											
Low	−0.473	−0.471	−0.471	−0.475	−0.478	−0.323	−0.453	−0.465	−0.462	−0.465	−0.464
Medium	−0.021	−0.022	−0.021	−0.022	−0.026	−0.023	−0.020	−0.028	−0.026	−0.022	−0.022
High	0.406	0.406	0.405	0.396	0.383	0.241	0.418	0.410	0.410	0.410	0.410

This table presents the average percentage returns and retail order imbalances one week before to after climate disasters for firms affected by them. Using retail order imbalances, we sort these CD firms into terciles around the climate disaster days. Then, for each tercile, we calculate the cross-sectional mean returns and take the time-series mean returns. Panels A and B generally report the time-series averages of the cross-sectional mean for returns and order imbalances, respectively. Instead, for the one day before to after climate disasters, including the disaster events (i.e., [−1], [0], [+1]), we present the cross-sectional average returns of the time-series means. Specifically, for both returns and order imbalances, as certain events may last more days, we take the mean for each event and CD firm in our sample. We then average across the events for each firm. Finally, we sort firms into terciles using order imbalances and take the cross-sectional mean returns. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Table 7: Long-Run Returns around Climate Disasters

	w − 6	w − 5	w − 4	w − 3	w − 2	w − 1	0	w + 1	w + 2	w + 3	w + 4	w + 5	w + 6
Panel A: Returns													
Low	−0.128	−0.175	−0.151	−0.223	−0.072	−0.175	0.214	−0.326	−0.269	−0.176	0.056	−0.172	−0.056
	−1.28	−2.60	−1.87	−1.15	−0.54	−1.98	5.09	−4.53	−3.77	−2.76	0.52	−1.17	−1.24
Medium	0.037	−0.103	−0.008	−0.189	0.105	0.103	0.253	−0.207	−0.089	0.027	0.253	−0.002	0.146
	0.29	−1.96	−0.09	−0.99	0.84	0.92	5.63	−2.06	−1.43	0.37	2.99	−0.01	2.79
High	0.049	0.141	0.109	0.014	0.144	−0.035	0.237	−0.097	0.031	0.158	0.217	0.051	0.222
	0.41	5.38	1.89	0.08	0.89	−0.21	4.33	−1.11	0.60	1.11	2.57	0.41	3.47
Panel B: Order imbalances													
Low	−0.476	−0.463	−0.474	−0.476	−0.454	−0.473	−0.323	−0.464	−0.483	−0.473	−0.486	−0.497	−0.505
Medium	−0.032	−0.029	−0.027	−0.029	−0.014	−0.021	−0.023	−0.022	−0.033	−0.027	−0.030	−0.039	−0.039
High	0.400	0.400	0.398	0.392	0.415	0.406	0.241	0.410	0.398	0.414	0.406	0.406	0.403

Note: This table presents the average percentage returns and retail order imbalances six weeks before and after climate disasters for firms affected by them. Using retail order imbalances, we sort these CD firms into terciles around the climate disaster days. Then for each tercile, we calculate the cross-sectional mean returns and, finally, take the time-series mean returns. Panels A and B generally report the time-series averages of the cross-sectional mean for returns and order imbalances, respectively. Instead, for climate disaster days (i.e., 0), we present the cross-sectional average returns of the time-series means. Specifically, for both returns and order imbalances, as certain events may last more days, we take the mean for each event and CD firm in our sample. We then average across the events for each firm. Finally, we sort firms into terciles using order imbalances and take the cross-sectional mean returns. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Table 8: Determinants of Retail Order Imbalances during Climate Disasters

Constant	−0.3984
	−7.81
Event dummy	0.0504
	1.78
Order imbalances (w−1)	0.1395
	25.80
Order imbalances (w−1)*Event dummy	−0.0527
	−1.93
Returns (w−1)	−0.7632
	−14.02
Returns (m−1)	−0.2725
	−11.89
Returns (m−7, m−2)	−0.0411
	−4.53
Turnover	0.0207
	1.76
Volatility	0.6079
	3.29
Size	0.0112
	4.90
B/M	−0.0131
	−4.55
Adj. R^2	2.80%

Note: This table presents the retail investors' trading activity determinants during climate disasters. The sample period is January 2010 to December 2018. We estimate Equation (1) using the Fama-MacBeth procedure, where the dependent variable is the one-week-ahead retail order imbalance measure. As independent variables, we include the order imbalances and returns over the previous week, one month, and six months. The event dummy equals one during climate disasters and zero otherwise. As control variables, we consider the previous month's turnover, volatility of daily returns, size (i.e., the logarithm of market capitalization), and the logarithm of book-to-market (B/M). We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 9: Retail Cumulative Abnormal Return Predictability around Climate Disasters

	CAR [1, 5]	CAR [1, 21]	CAR [1, 42]	CAR [1, 63]
Order imbalances	0.0019	0.0119	0.0153	0.0217
	1.28	2.57	1.81	1.75
Returns	−0.0324	−0.2019	−0.2354	−0.4515
	−1.19	−2.43	−1.55	−2.03
Turnover	−0.0299	−0.0695	−0.1897	−0.2116
	−2.35	−1.78	−2.67	−2.03
Volatility	−0.2094	−0.0125	0.9597	0.5939
	−1.58	−0.03	1.30	0.55
Size	−0.0155	−0.0692	−0.1116	−0.1843
	−3.66	−5.34	−4.71	−5.32
B/M	0.0105	0.0241	0.0302	0.0403
	2.51	1.88	1.29	1.18
R^2	61.67%	65.53%	66.54%	65.79%

Note: This table presents the cumulative abnormal return predictability around climate disasters. The sample period is January 2010 to December 2018. We estimate a panel regression with firm, month, and year fixed effects using Equation (2). The dependent variable is the one-week, one-month, two-month, and three-month ahead cumulative abnormal returns (CAR) around climate disasters. The independent variables include the order imbalances and returns over the previous week, excluding the event days. As control variables, we consider the previous month's turnover, volatility of daily returns, size (i.e., the logarithm of market capitalization), and the logarithm of book-to-market (B/M).

Table 10: Retail Return Predictability during Climate Disasters

	[1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]	w=2	w=4	w=6	w=8	w=10	w=12
Constant	0.0016	0.0018	0.0022	0.0019	0.0014	0.0019	−0.0018	−0.0026	0.0053	0.0081	0.0038
	1.27	0.82	0.71	0.47	0.29	0.37	−0.33	−0.54	1.19	1.55	0.72
Event dummy	−0.0007	−0.0012	−0.0017	−0.0021	−0.0025	−0.0003	−0.0021	−0.0028	0.0014	0.0008	0.0004
	−1.40	−1.34	−1.44	−1.54	−1.68	−0.21	−1.57	−2.42	0.79	0.44	0.28
Order imbalances (w−1)	0.0002	0.0003	0.0005	0.0007	0.0008	0.0005	0.0004	0.0004	0.0001	0.0002	0.0002
	6.11	6.79	7.48	7.89	7.53	3.90	3.48	2.88	0.80	1.76	1.59
Order imbalances (w−1)*Event dummy	−0.0001	−0.0002	−0.0003	0.0000	−0.0004	0.0012	0.0008	0.0013	−0.0040	0.0001	0.0008
	−0.20	−0.17	−0.18	0.01	−0.22	0.79	0.57	1.02	−1.95	0.04	0.50
Order imbalances (m−1)	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002	0.0002	0.0001	0.0000	0.0001	0.0001
	5.53	4.84	4.94	4.83	4.81	4.18	3.10	2.40	0.65	2.43	2.21
Order imbalances (m−1)*Event dummy	−0.0003	−0.0007	−0.0009	−0.0012	−0.0015	−0.0002	0.0004	−0.0012	0.0008	0.0001	0.0003
	−1.44	−1.93	−1.73	−1.88	−2.09	−0.36	0.53	−2.16	1.07	0.18	0.46
Order imbalances (m−7, m−2)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	1.05	1.44	1.42	1.06	0.69	−0.33	−1.00	−0.11	−0.64	−1.58	−1.08
Order imbalances (m−7, m−2)*Event dummy	0.0000	0.0002	0.0003	0.0003	0.0004	−0.0001	−0.0001	0.0000	0.0001	0.0002	0.0003
	0.77	1.56	1.84	1.88	1.79	−0.24	−0.79	−0.25	0.59	1.03	1.45
Returns (w−1)	−0.0177	−0.0241	−0.0276	−0.0290	−0.0295	−0.0014	−0.0107	0.0002	0.0073	0.0011	−0.0009
	−6.14	−6.84	−6.40	−5.70	−4.77	−0.21	−2.39	0.04	1.47	0.25	−0.23
Returns (m−1)	−0.0016	−0.0028	−0.0035	−0.0033	−0.0033	−0.0025	−0.0035	0.0007	−0.0005	0.0025	0.0044
	−1.55	−1.43	−1.29	−0.99	−0.85	−0.68	−0.88	0.18	−0.18	0.78	1.37
Returns (m−7, m−2)	0.0004	0.0009	0.0013	0.0018	0.0024	0.0015	0.0000	0.0006	0.0005	0.0011	0.0004
	1.19	1.58	1.77	2.01	2.36	1.43	0.01	0.46	0.38	0.86	0.37
Turnover	−0.0004	−0.0008	−0.0015	−0.0024	−0.0030	−0.0003	−0.0034	−0.0034	−0.0002	−0.0005	−0.0028
	−0.79	−1.00	−1.30	−1.59	−1.65	−0.13	−1.67	−2.09	−0.08	−0.24	−1.40
Volatility	0.0003	0.0029	0.0046	0.0030	0.0040	0.0152	0.0248	−0.0095	−0.0332	−0.0070	−0.0085
	0.04	0.20	0.23	0.12	0.14	0.57	0.71	−0.29	−1.18	−0.27	−0.30
Size	−0.00005	−0.00005	−0.0001	−0.0001	−0.00001	0.00003	0.0001	0.0001	−0.0002	−0.0002	0.0000
	−0.73	−0.41	−0.44	−0.27	−0.05	0.12	0.35	0.37	−0.72	−0.65	−0.16
B/M	0.00001	0.00005	0.0001	0.0001	0.00002	−0.0005	−0.00002	0.0003	0.0005	0.0001	0.0006
	0.14	0.24	0.29	0.19	0.06	−1.37	−0.04	0.71	1.35	0.37	1.64
Adj. R^2	3.63%	3.90%	4.04%	4.06%	4.02%	3.97%	3.71%	3.17%	3.08%	2.99%	3.09%

Note: This table presents the return predictability of the retail order imbalances during climate disasters. The sample period is January 2010 to December 2018. We estimate Equation (3) using the Fama-MacBeth procedure. The dependent variables are the short run and w-weeks ahead returns, and the independent variables include the order imbalances and returns over the previous week, month, and six months. The event dummy equals one during climate disasters and zero otherwise. As control variables, we consider the previous month's turnover, volatility of daily returns, size (i.e., the logarithm of market capitalization), and the logarithm of book-to-market (B/M). We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 11: Analysts' Earnings Forecast Error Predictability during Climate Disasters

	[1, 2]	[1, 3]	[1, 5]	[6, 20]
Constant	−7.0643	−6.6268	−6.0692	−8.4738
	−7.40	−5.97	−6.21	−9.86
Event dummy	−0.7356	−0.5238	−0.0055	−0.5657
	−1.73	−1.25	−0.12	−4.79
Order imbalances [0]	0.3081	0.1999	0.1547	−0.0380
	3.11	3.45	2.90	−1.51
Order imbalances [0] * Event dummy	−0.2558	−0.2508	−0.3830	0.1469
	−1.25	−1.51	−2.52	0.75
Returns [0]	3.0063	1.7713	1.1007	0.0046
	5.73	1.97	1.70	0.01
Returns [−5, −1]	0.3326	0.3567	−0.0566	−0.0251
	0.60	0.56	−0.09	−0.08
Returns [−26, −6]	−0.5202	−0.5909	−0.8521	−0.1516
	−4.27	−6.38	−2.88	−0.67
Size	0.1925	0.1916	0.1757	0.2807
	3.92	3.44	3.46	6.51
B/M	0.0061	0.00664	−0.0021	0.0203
	0.23	0.22	−0.05	0.34
Adj. R^2	1.46%	1.91%	2.50%	3.90%

Note: This table presents the analysts' earnings forecast error predictability of the retail order imbalances during climate disasters. The sample period is January 2010 to December 2018. We estimate Equation (4) using the Fama-MacBeth procedure with the logistic regression model, where the forecast error is the difference between actual earnings-per-share and the median I/B/E/S analyst forecast. The dependent variable is the forecast error dummy equal to one when the forecast error over days $t + x$ and $t + y$ is positive and zero otherwise. The independent variables include the order imbalances and returns on day zero and the previous week and month returns. The event dummy equals one during climate disasters and zero otherwise. As control variables, we consider the previous month's size (i.e., the logarithm of market capitalization) and the logarithm of book-to-market (B/M). Following Kelley and Tetlock (2013), we require at least 50 earnings announcements for each daily logistic regression. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 12: Strategy Returns during Climate Disasters

Panel A: Short run strategy

	[1]		[1, 2]		[1, 3]		[1, 4]		[1, 5]	
	CD	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**
Low	0.045	−0.012	0.056	−0.011	0.011	−0.069	0.068	−0.077	0.169	−0.025
	0.61	−0.23	0.41	−0.12	0.06	−0.48	0.28	−0.44	0.66	−0.12
High	−0.069	−0.001	−0.144	0.008	−0.315	−0.051	−0.314	−0.041	−0.198	0.014
	−0.94	−0.01	−0.93	0.09	−1.32	−0.36	−1.06	−0.23	−0.62	0.07
High − Low	−0.115	0.011	−0.199	0.020	−0.326	0.018	−0.382	0.036	−0.367	0.039
	−1.57	1.13	−1.62	1.08	−1.92	0.68	−1.71	1.08	−1.45	1.02

Panel B: Long run strategy

	w=2		w=4		w=6		w=8		w=10		w=12	
	CD	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**
Low	0.487	0.144	0.499	0.187	−0.108	0.290	−0.562	0.585	0.138	1.191	0.619	1.842
	1.31	0.49	0.90	0.42	−0.13	0.56	−0.50	1.10	0.11	1.98	0.45	2.75
High	−0.004	0.189	0.415	0.414	0.604	0.653	1.433	1.141	2.595	1.879	3.057	2.665
	−0.01	0.63	0.51	0.91	0.56	1.28	1.43	2.23	2.53	3.22	2.66	4.22
High − Low	−0.492	0.046	−0.085	0.226	0.712	0.363	1.995	0.555	2.457	0.688	2.437	0.823
	−1.33	0.83	−0.12	2.58	0.70	3.01	1.65	3.70	1.90	3.88	1.88	4.46

Note: This table presents the short and long-run portfolio returns and the high−low strategy returns during climate disasters for firms affected (CD) and non-affected (non-CD) by them. In particular, using the previous week's retail order imbalance on each climate disaster day, we sort firms into two groups. Then for each group, we consider the CD and non-CD firms. The long−short strategy consists in buying the stocks with the highest order imbalance and selling stocks with the lowest order imbalance. The sample period is January 2010 to December 2018. Panels A and B report the percentage value-weighted portfolio returns based on the previous month's market capitalization in the short and long run. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 13: Return Comovement Estimates on the Low, High and High − Low Return Portfolios and their Relationship during Climate Disasters

	CD	Non-CD
Panel A		
Low return comovement	0.9690	1.0097
	22.44	322.68
High return comovement	0.9161	0.9632
	20.17	199.46
High − Low return comovement	0.1994	0.3733
	1.21	2.65
Panel B		
Low return comovement	0.8900	1.0668
	20.79	80.66
High return comovement	0.8543	1.0114
	20.44	83.22
High − Low return comovement	0.3388	0.2897
	2.03	1.93

Note: This table presents the relationship between the return comovement estimates on the low, high, and high−low return portfolios during climate disasters. In particular, we sort firms into two groups each climate disaster day using the previous week's retail order imbalance. We compute the value-weighted portfolio returns based on the previous month's market capitalization. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily return comovement coefficients by using a forward-looking 30-day window to estimate the rolling regression model of Equation (5) for each of the low, high, and high−low portfolios. The dependent variable is the firm's returns, and the independent variable includes the portfolio returns. Panel A reports the value-weighted comovement coefficients based on the previous month's market capitalization for firms affected (CD) and non-affected (non-CD) by a climate disaster. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 14: Climate Disaster Return Comovement Estimates on the Climate Disaster Low, High and High − Low Return Portfolios and their Relationship during Climate Disasters

	Low			High			High − Low		
	CD	Non-CD	Difference	CD	Non-CD	Difference	CD	Non-CD	Difference
Panel A									
CD comovement	0.0534	0.0673	−0.0139	0.1321	0.0749	0.0572	−0.0427	−0.0297	−0.0131
	1.09	3.83	−0.29	2.76	4.63	1.19	−1.28	−2.59	−0.37
Non-CD comovement	0.2318	0.4865	−0.2547	0.7036	0.5237	0.1799	−0.4538	−0.1504	−0.3035
	0.85	11.65	−0.94	3.01	15.53	0.77	−1.10	−2.04	−0.72
Panel B									
CD comovement	0.2165	0.0766	0.1362	0.2702	0.0632	0.2038	−0.0810	−0.0319	−0.0472
	4.79	3.98	3.52	7.45	3.38	5.40	−2.90	−1.75	−1.67
Non-CD comovement	0.5933	0.7473	−0.1586	1.0060	0.7429	0.2586	−0.6411	−0.0774	−0.5492
	2.22	47.30	−0.59	4.20	45.56	1.07	−1.45	−1.22	−1.24

Note: This table presents the relationship between return comovement estimates of firms affected (CD) and non-affected (non-CD) by a climate disaster on their low, high, and high−low return portfolios during climate disasters. In particular, we sort firms into two groups on each climate disaster day using the previous week's retail order imbalance. Then for each group, we consider the CD and non-CD firms. We compute the value-weighted portfolio returns based on the previous month's market capitalization. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily return comovement coefficients of CD and non-CD firms by using a forward-looking 30-day window to estimate a rolling regression model as in Equations (6) and (7) for each of the CD and non-CD low, high, and high−low portfolios. The dependent variable is the firm's returns, and the independent variable includes the portfolio returns. Panel A reports the value-weighted CD and non-CD comovement coefficients based on the previous month's market capitalization during climate disasters for CD and non-CD firms. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 15: Order Imbalance Comovement Estimates on the Low, High and High − Low Order Imbalance Portfolios and their Relationship during Climate Disasters

	CD	**Non-CD**
Panel A		
Low imbalances comovement	0.7034	0.5238
	3.01	15.49
High imbalances comovement	0.2422	0.4855
	0.90	11.57
High − Low imbalances comovement	−0.4702	−0.1477
	−1.13	−2.00
Panel B		
Low imbalances comovement	1.0064	0.7428
	4.20	45.30
High imbalances comovement	0.6193	0.7500
	2.34	47.44
High − Low imbalances comovement	−0.6073	−0.0626
	−1.36	−1.01

Note: This table presents the relationship between the order imbalance comovement estimates on the low, high, and high−low return portfolios during climate disasters. In particular, we sort firms into two groups each climate disaster day using the previous week's retail order imbalance. We compute equal-weighted order imbalance portfolios. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily order imbalance comovement coefficients by using a forward-looking 30-day window to estimate the rolling regression model of Equation (8) for each of the low, high, and high−low portfolios. The dependent variable is the firm's order imbalances, and the independent variable includes the retail order imbalances portfolio. Panel A reports the value-weighted comovement coefficients based on the previous month's market capitalization for firms affected (CD) and non-affected (non-CD) by a climate disaster. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Table 16: Climate Disaster Order Imbalance Comovement Estimates on the Climate Disaster Low, High and High − Low Order Imbalance Portfolios and their Relationship during Climate Disasters

	Low			High			High − Low		
	CD	**Non-CD**	**Difference**	**CD**	**Non-CD**	**Difference**	**CD**	**Non-CD**	**Difference**
Panel A									
CD comovement	0.0536	0.0671	−0.0134	0.1392	0.0824	0.0568	−0.0396	−0.0365	−0.0032
	1.03	3.40	−0.26	2.84	4.85	1.14	−1.16	−2.90	−0.08
Non-CD comovement	0.2214	0.4753	−0.2539	0.6851	0.5350	0.1501	−0.4272	−0.1830	−0.2443
	0.79	10.83	−0.90	2.89	15.67	0.64	−1.03	−2.41	−0.59
Panel B									
CD comovement	0.2231	0.0840	0.1352	0.2690	0.0660	0.1999	−0.0784	−0.0318	−0.0445
	4.56	3.63	3.06	7.43	3.54	5.31	−2.54	−1.69	−1.48
Non-CD comovement	0.5817	0.7531	−0.1749	0.9953	0.7503	0.2407	−0.6720	−0.0828	−0.5748
	2.17	46.57	−0.65	4.01	42.30	0.96	−1.50	−1.34	−1.29

Note: This table presents the relationship between the order imbalance comovement estimates of firms affected (CD) and non-affected (non-CD) by a climate disaster on their low, high, and high−low order imbalance portfolios during climate disasters. In particular, we sort firms into two groups on each climate disaster day using the previous week's retail order imbalance. Then for each group, we consider the CD and non-CD firms. We compute equal-weighted order imbalance portfolios. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily order imbalance comovement coefficients of CD and non-CD firms by using a forward-looking 30-day window to estimate a similar rolling regression model as in Equations (9) and (10) for each of the CD and non-CD low, high, and high−low portfolios. The dependent variable is the firm's order imbalances, and the independent variable includes the retail order imbalances portfolio. Panel A reports the value-weighted CD and non-CD comovement coefficients based on the previous month's market capitalization during climate disasters for CD and non-CD firms. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.1: Retail Investors' Activity during Climate Disaster and Non-Climate Disaster Days considering the State

	Climate disaster	Non climate disaster	Difference
Panel A: Same state			
Order imbalances	−0.036	−0.025	−0.011
	−5.99	−6.80	−1.57
Buy volume	34162	37400	−3238
	13.16	12.34	−2.21
Sell volume	33872	37230	−3358
	13.39	12.59	−2.37
Total volume	68034	74630	−6596
	13.32	12.49	−2.33
Panel B: Other states			
Order imbalances	−0.036	−0.031	−0.005
	−6.08	−33.22	−0.94
Buy volume	33739	36886	−3147
	13.40	13.31	−2.22
Sell volume	33502	36824	−3322
	13.64	13.60	−2.45
Total volume	67242	73710	−6469
	13.56	13.46	−2.36

Note: This table presents the cross-sectional averages of the time-series means for retail investors' trading activity, i.e., order imbalances, buy and sell volume, total volume, and their difference, during climate and non-climate disaster days. Panels A and B report these averages for the firms affected and non-affected by a climate disaster within the same state and other states (excluding the climate disaster state). In particular, we calculate the time-series average for each retail measure during climate and non-climate disaster days for each stock in our sample and then take the cross-sectional mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Appendix A.2: Retail Investors' Activity during Climate Disasters considering the State

	CD	Non-CD	Difference
Panel A: Same state			
Order imbalances	−0.031	−0.030	−0.001
	−2.94	−6.00	−0.06
Buy volume	29019	37993	−8974
	12.96	15.81	−3.38
Sell volume	29470	37469	−7999
	12.69	16.04	−3.08
Total volume	58489	75462	−16973
	12.88	15.96	−3.25
Panel B: Other states			
Order imbalances	−0.031	−0.034	0.004
	−2.94	−16.53	0.37
Buy volume	29019	42912	−13892
	12.96	48.02	−5.73
Sell volume	29470	43239	−13769
	12.69	47.68	−5.64
Total volume	58489	86151	−27661
	12.88	48.17	−5.71

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy and sell volume, total volume, and their difference, during climate disaster days for firms affected (CD) and non-affected (non-CD) by them. Panels A and B report these averages for the CD and non-CD firms within the same state and other states (excluding the climate disaster state). In particular, we calculate the cross-sectional mean for each retail measure during climate disaster days for CD and non-CD firms in our sample and then take the time-series mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Appendix A.3: Retail Investors' Activity before and after Climate Disasters

	Before	After	Difference
Panel A: One month before and after climate disasters			
Order imbalances	−0.029	−0.032	0.003
	−10.39	−11.32	0.78
Buy volume	37396	33940	3455
	81.52	83.74	5.66
Sell volume	36967	33943	3024
	77.67	89.68	5.00
Total volume	74363	67884	6479
	84.31	89.31	5.58
Panel B: Three months before and after climate disasters			
Order imbalances	−0.031	−0.036	0.005
	−18.45	−17.86	1.81
Buy volume	36549	34169	2380
	124.34	140.66	6.25
Sell volume	36595	34238	2357
	136.06	151.66	6.72
Total volume	73144	68407	4737
	138.08	155.23	6.88

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy and sell volume, and total volume. Panels A and B report these averages and their difference one month before and after climate disasters for CD firms and three months before and after (including the event period), respectively. We calculate the cross-sectional mean for each retail measure around climate disaster days in our sample and then take the time-series mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Appendix A.4: Retail Investors' Activity on Non-CD Firms around Climate Disasters

Panel A: One week before to after climate disasters	[−5, −1]	[−4, −1]	[−3, −1]	[−2, −1]	[−1]	0	[1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]
Order imbalances	−0.032	−0.033	−0.032	−0.031	−0.032	−0.030	−0.028	−0.033	−0.033	−0.032	−0.033
	−17.21	−22.61	−23.53	−26.00	−111.09	−139.36	−87.96	−6.64	−11.53	−13.89	−15.30
Buy volume	44719	44326	44674	43480	43376	40110	42640	42420	42371	42876	42917
	55.22	48.51	37.39	418.90	296.36	332.31	270.37	192.49	310.47	83.39	107.19
Sell volume	43924	43852	43876	43084	43355	39986	42626	42651	42774	43212	43278
	98.06	76.83	54.40	158.88	303.51	333.82	249.34	1696.72	343.34	96.90	123.06
Total volume	88643	88178	88549	86565	86732	80096	85266	85071	85145	86087	86194
	72.77	60.68	44.57	517.15	304.04	334.44	260.84	435.73	630.49	90.90	116.27

	Before	After	Difference
Panel B: One month before and after climate disasters			
Order imbalances	−0.031	−0.038	0.007
	−24.40	−20.75	2.95
Buy volume	45696	42175	3521
	107.13	157.47	7.06
Sell volume	44902	42626	2276
	108.80	141.99	4.49
Total volume	90598	84801	5797
	111.88	158.72	6.03
Panel C: Three months before and after climate disasters			
Order imbalances	−0.032	−0.037	0.005
	−34.49	−21.87	2.58
Buy volume	44962	42727	2235
	184.75	201.46	6.93
Sell volume	44830	43157	1672
	167.70	220.40	5.06
Total volume	89791	85884	3907
	183.94	225.13	6.32

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy and sell volume, and total volume. Panel A reports the averages for the one week before to after climate disasters for non-CD firms, i.e., those not affected by them. Panels B and C report the averages and their difference one month before and after climate disasters and three months before and after (including the event period), respectively. We calculate the cross-sectional mean for each retail measure around climate disaster days in our sample and then take the time-series mean. Instead, for the climate disaster days (i.e., 0), we present the cross-sectional average of the time-series means for retail investors' trading activity. Specifically, as certain events may take more days, we take the mean for each event and non-CD firm in our sample, then average across the events for each firm, and finally, the cross-sectional mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Appendix A.5: Retail Investors' Activity around Climate Disasters by Event

	[−5, −1]	[−4, −1]	[−3, −1]	[−2, −1]	[−1]	0	[1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]
Panel A: Drought											
Order imbalances	−0.048	−0.054	−0.058	−0.044	−0.062	−0.035	−0.035	−0.001	−0.011	−0.007	0.018
	−4.35	−4.37	−3.43	−2.47	−1.29	−1.99	−0.78	−0.02	−0.48	−0.42	0.65
Buy volume	41988	43038	42593	37395	32836	44411	41082	38020	36298	37444	37922
	12.43	10.39	7.31	8.20	2.85	2.77	3.08	12.41	14.71	17.93	22.49
Sell volume	40631	43038	41538	38123	29564	42325	41949	38340	37806	37865	38067
	9.59	9.55	6.92	4.45	3.16	2.90	2.98	10.62	17.57	24.87	31.82
Total volume	82619	86076	84131	75518	62401	86736	83031	76360	74104	75309	75988
	11.28	10.32	7.34	5.76	3.01	2.83	3.03	11.45	16.60	22.29	28.10
Panel B: Flooding											
Order imbalances	−0.023	−0.022	−0.020	−0.027	−0.034	−0.030	−0.015	−0.029	−0.025	−0.020	−0.020
	−5.03	−3.88	−2.65	−3.87	−3.06	−3.88	−1.33	−2.02	−2.86	−2.48	−3.15
Buy volume	40791	40582	40121	39175	40377	37168	37074	38316	38110	39405	39845
	53.38	42.76	34.21	32.60	9.35	10.92	10.91	30.87	51.12	28.18	34.09
Sell volume	40296	40402	39411	38037	38415	35875	36020	37359	37557	38585	38719
	37.09	28.94	28.34	100.84	9.58	11.30	12.24	27.89	47.05	32.90	42.16
Total volume	81086	80984	79532	77212	78791	73042	73094	75675	75667	77990	78564
	45.77	35.46	31.92	48.90	9.52	11.15	11.65	29.32	50.78	30.58	38.18
Panel C: Hail											
Order imbalances	−0.013	−0.005	−0.001	0.002	0.013	−0.019	−0.054	−0.058	−0.047	−0.047	−0.041
	−1.36	−0.76	−0.11	0.21	0.51	−1.12	−2.08	−13.51	−4.16	−5.93	−4.71
Buy volume	43989	44501	46134	43799	43472	37142	49698	47863	45873	46373	48098
	23.48	19.13	19.69	133.86	5.43	6.57	5.08	26.08	20.35	27.76	22.30
Sell volume	43609	42977	42761	42008	45269	39582	48977	45613	45504	46118	46093
	33.84	29.64	21.09	12.88	5.76	5.92	5.34	13.56	23.40	30.62	39.50
Total volume	87598	87478	88895	85807	88741	76724	98675	93476	91378	92491	94191
	39.41	30.53	25.24	29.25	5.85	6.28	5.30	17.98	24.95	32.81	34.03
Panel D: Hurricane/Tropical Storm											
Order imbalances	−0.004	−0.009	−0.004	−0.007	−0.013	−0.019	−0.027	0.000	−0.019	−0.015	−0.015
	−0.63	−1.57	−0.96	−1.03	−0.55	−1.23	−1.06	−0.01	−0.78	−0.89	−1.12
Buy volume	30008	30947	31650	32001	31382	34430	32322	36662	37645	36310	34567
	26.80	39.29	63.22	51.68	7.72	7.03	4.11	8.45	13.98	15.62	13.79
Sell volume	31571	32989	33307	33832	33015	35506	31578	37346	38668	36828	35349
	21.18	55.76	47.20	41.42	7.85	7.03	4.88	6.47	10.79	11.76	12.44
Total volume	61579	63936	64957	65832	64397	69936	63900	74009	76313	73138	69916
	23.94	48.05	53.88	45.85	7.97	7.08	4.51	7.32	12.16	13.40	13.16
Panel E: Tornado											
Order imbalances	−0.062	−0.052	−0.054	−0.066	−0.072	−0.042	−0.016	−0.027	−0.040	−0.046	−0.046
	−5.00	−5.68	−4.28	−9.76	−3.11	−2.43	−0.67	−2.40	−2.76	−3.83	−4.92
Buy volume	34973	35379	36139	35539	34125	30172	28109	28397	29130	29020	29538
	38.64	33.89	35.67	25.13	5.96	6.88	7.04	98.86	38.74	53.45	44.28
Sell volume	35669	35366	35340	35332	32374	30260	28414	29578	32714	33284	33189
	36.27	29.28	20.69	11.94	7.37	6.81	7.67	25.41	10.20	14.24	18.30
Total volume	70641	70746	71478	70871	66499	60432	56523	57975	61844	62304	62727
	46.03	35.79	27.53	16.21	6.72	7.04	7.50	39.94	15.62	21.96	28.03

(continued)

Appendix A.5 (continued): Retail Investors' Activity around Climate Disasters by Event

	[−5, −1]	[−4, −1]	[−3, −1]	[−2, −1]	[−1]	0	[1]	[1, 2]	[1, 3]	[1, 4]	[1, 5]
Panel F: Wildfire											
Order imbalances	0.003	−0.009	−0.018	−0.021	−0.066	0.000	−0.003	−0.011	0.016	0.007	0.014
	0.14	−0.46	−0.71	−0.47	−1.95	0.01	−0.09	−1.45	0.57	0.34	0.79
Buy volume	49344	52536	53250	46121	35951	39587	49980	46423	44767	46100	45754
	8.21	8.00	5.77	4.53	3.03	3.23	2.49	13.05	16.97	20.10	25.28
Sell volume	48938	51126	51858	44912	37939	43357	52079	47927	47142	46120	44599
	9.90	8.93	6.46	6.44	2.91	3.18	2.67	11.54	18.69	22.44	20.25
Total volume	98283	103661	105108	91032	73889	82944	102060	94349	91909	92221	90353
	9.01	8.46	6.11	5.31	2.97	3.21	2.58	12.24	18.10	25.59	26.90
Panel G: Wind											
Order imbalances	−0.042	−0.046	−0.054	−0.044	−0.058	−0.046	−0.003	−0.019	−0.017	−0.019	−0.026
	−4.02	−3.71	−4.18	−3.13	−3.16	−3.37	−0.16	−1.17	−1.69	−2.59	−2.96
Buy volume	33985	33413	34072	30973	30345	33220	35655	33153	33222	35297	34851
	18.14	14.51	10.92	49.31	6.81	6.54	6.24	13.25	22.97	15.26	18.88
Sell volume	33940	33592	34473	32230	31905	31903	33704	32652	33758	35762	35633
	23.38	18.46	15.31	99.23	7.08	7.34	6.70	31.06	26.77	16.30	20.91
Total volume	67925	67005	68546	63203	62250	65123	69359	65805	66980	71059	70484
	20.55	16.35	12.76	66.33	6.99	6.97	6.51	18.52	28.33	16.12	20.36
Panel H: Winter Weather											
Order imbalances	−0.025	−0.015	−0.005	0.032	0.028	−0.052	−0.010	−0.008	−0.003	0.004	−0.004
	−1.04	−0.53	−0.15	9.42	0.58	−1.74	−0.24	−3.36	−0.48	0.54	−0.39
Buy volume	31891	32132	34819	35478	37195	25081	27529	25742	23938	27288	26668
	14.53	11.41	29.25	20.66	2.36	3.26	3.33	14.41	11.52	7.46	9.19
Sell volume	30514	31587	33653	33145	37296	24452	22426	23471	23046	23252	22903
	13.00	11.72	13.74	7.98	2.25	3.33	3.93	22.46	31.22	41.42	41.05
Total volume	62406	63719	68472	68623	74491	49534	49955	49214	46984	50540	49571
	14.42	11.97	20.19	11.69	2.31	3.30	3.64	66.38	20.69	12.95	15.62

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy and sell volume, total volume, one week before to after each climate disaster for firms affected by them. We calculate the cross-sectional mean for each retail measure around climate disaster days in our sample and then take the time-series mean. Instead, for the climate disaster days (i.e., 0), we present the cross-sectional average of the time-series means for retail investors' trading activity. Specifically, as certain events may last more days, we take the mean for each event and CD firm in our sample, then average across the events for each firm and finally the cross-sectional mean. The sample period is January 2010 to December 2018. We compute the retail measures using the sub-penny price improvement approach of Boehmer et al. (2021). The order imbalance measure is the difference between the retail buy and sell volume divided by the sum of retail buy and sell volume.

Appendix A.6: Retail Return Predictability during Climate Disasters

	[1]	[1,2]	[1,3]	[1,4]	[1,5]	w=2	w=4	w=6	w=8	w=10	w=12
Constant	0.0013	0.0015	0.0019	0.0013	0.0008	0.0027	−0.0002	−0.0027	0.0046	0.0088	0.0040
	1.08	0.72	0.63	0.34	0.18	0.57	−0.04	−0.57	1.04	1.76	0.80
Event dummy	−0.0006	−0.0011	−0.0016	−0.0019	−0.0018	0.0005	−0.0015	−0.0017	0.0007	−0.0001	0.0016
	−1.88	−1.83	−1.92	−1.91	−1.50	0.35	−1.24	−1.37	0.54	−0.04	1.16
Order imbalances (m−1)	0.0001	0.0002	0.0003	0.0004	0.0004	0.0003	0.0003	0.0002	0.0000	0.0001	0.0001
	9.16	9.06	9.21	8.96	8.65	5.97	5.56	3.42	0.39	1.59	2.60
Order imbalances (m−1)*Event dummy	−0.0002	−0.0005	−0.0008	−0.0011	−0.0014	−0.0007	0.0002	−0.0006	0.0006	0.0019	−0.0001
	−1.24	−1.69	−2.09	−2.23	−2.36	−1.13	0.47	−1.15	0.94	2.73	−0.12
Returns (w−1)	−0.0189	−0.0249	−0.0287	−0.0300	−0.0307	−0.0025	−0.0110	−0.0003	0.0058	−0.0006	−0.0024
	−6.73	−7.06	−6.53	−5.70	−4.93	−0.39	−2.49	−0.09	1.21	−0.14	−0.61
Returns (m−1)	−0.0014	−0.0023	−0.0028	−0.0028	−0.0026	−0.0019	−0.0036	0.0004	−0.0008	0.0025	0.0041
	−1.35	−1.22	−1.09	−0.86	−0.70	−0.54	−0.91	0.11	−0.27	0.81	1.33
Returns (m−7,m−2)	0.0003	0.0009	0.0013	0.0018	0.0024	0.0012	−0.0001	0.0006	0.0001	0.0013	0.0004
	1.20	1.69	1.82	2.08	2.41	1.20	−0.07	0.47	0.11	1.13	0.33
Turnover	−0.0004	−0.0008	−0.0014	−0.0022	−0.0028	−0.0009	−0.0034	−0.0034	−0.0007	−0.0003	−0.0031
	−0.98	−0.98	−1.16	−1.45	−1.52	−0.44	−1.74	−2.04	−0.38	−0.13	−1.57
Volatility	−0.0006	0.0012	0.0021	0.0028	0.0035	0.0173	0.0221	−0.0124	−0.0353	−0.0076	−0.0042
	−0.08	0.09	0.11	0.12	0.13	0.70	0.68	−0.40	−1.33	−0.31	−0.15
Size	0.0000	−0.0001	−0.0001	−0.00004	0.00000	−0.00002	0.0000	0.0001	−0.0001	−0.0002	0.0000
	−0.71	−0.45	−0.46	−0.22	0.00	−0.08	0.11	0.50	−0.53	−0.74	−0.14
B/M	0.0001	0.0001	0.0001	0.0001	0.0001	−0.0005	−0.00007	0.0003	0.0006	0.0002	0.0006
	0.64	0.51	0.49	0.37	0.24	−1.38	−0.17	0.75	1.49	0.49	1.82
Adj. R^2	3.63%	3.91%	4.04%	4.03%	3.97%	3.84%	3.68%	3.23%	3.10%	2.91%	3.08%

Note: This table presents the return predictability of the retail order imbalances during climate disasters. The sample period is January 2010 to December 2018. Using the Fama-MacBeth procedure, we estimate a regression similar to Equation (3) only with the past one-month order imbalances and the other control variables akin to Table 10. The dependent variables are the short run and w-weeks ahead returns. The independent variables include the order imbalances over the previous month and returns over the previous week, month, and six months. The event dummy equals one during climate disasters and zero otherwise. As control variables, we consider the previous month's turnover, volatility of daily returns, size (i.e., the logarithm of market capitalization), and the logarithm of book-to-market (B/M). We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.7: Strategy Alphas during Climate Disasters

Panel A: Short run strategy

	[1]		[1, 2]		[1, 3]		[1, 4]		[1, 5]	
	CD	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**
Low	0.038	−0.020	0.048	−0.023	0.018	−0.075	0.067	−0.083	0.173	−0.031
	0.52	−0.38	0.35	−0.24	0.09	−0.52	0.28	−0.47	0.66	−0.15
High	−0.075	−0.007	−0.150	−0.001	−0.316	−0.053	−0.305	−0.044	−0.194	0.011
	−1.04	−0.15	−0.99	−0.01	−1.32	−0.37	−1.03	−0.25	−0.60	0.05
High−Low	−0.112	0.012	−0.198	0.022	−0.334	0.021	−0.372	0.039	−0.366	0.042
	−1.59	1.19	−1.63	1.22	−1.96	0.79	−1.69	1.18	−1.45	1.09

Panel B: Long run strategy

	w=2		w=4		w=6		w=8		w=10		w=12	
	CD	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**	**CD**	**Non-CD**
Low	0.491	0.134	0.523	0.192	−0.075	0.296	−0.540	0.585	0.161	1.198	0.668	1.862
	1.31	0.46	0.94	0.43	−0.09	0.58	−0.48	1.11	0.12	1.98	0.49	2.79
High	−0.018	0.181	0.399	0.415	0.604	0.657	1.433	1.137	2.611	1.883	3.090	2.683
	−0.04	0.60	0.48	0.91	0.56	1.28	1.43	2.23	2.53	3.20	2.69	4.27
High−Low	−0.509	0.047	−0.124	0.224	0.679	0.361	1.973	0.552	2.450	0.685	2.422	0.821
	−1.38	0.85	−0.18	2.58	0.67	3.01	1.63	3.68	1.89	3.85	1.88	4.42

Note: This table presents the short and long-run portfolio alphas and the high−low strategy alphas during climate disasters for firms affected (CD) and non-affected (non-CD) by them. In particular, using the previous week's retail order imbalance on each climate disaster day, we sort firms into two groups. Then for each group, we consider the CD and non-CD firms. The long−short strategy consists in buying the stocks with the highest order imbalance and selling stocks with the lowest order imbalance. The sample period is January 2010 to December 2018. Panels A and B report the percentage value-weighted portfolio returns based on the previous month's market capitalization in the short and long run. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.8: Strategy Returns and its Relationship with Climate Disasters

Panel A: Short run strategy					
	[1]	**[1, 2]**	**[1, 3]**	**[1, 4]**	**[1, 5]**
Low	0.046	0.092	0.139	0.183	0.228
	2.43	2.57	2.72	2.80	2.93
High	0.059	0.118	0.175	0.233	0.285
	3.07	3.19	3.28	3.43	3.53
High − Low	0.014	0.026	0.035	0.050	0.057
	2.88	2.99	2.89	3.29	3.13

Panel B: Long run strategy						
	w=2	**w=4**	**w=6**	**w=8**	**w=10**	**w=12**
Low	0.467	0.958	1.453	1.961	2.458	2.948
	3.88	5.59	7.13	8.56	9.49	10.61
High	0.550	1.123	1.677	2.235	2.772	3.344
	4.42	6.41	7.96	9.48	10.50	11.96
High − Low	0.083	0.164	0.224	0.274	0.315	0.396
	3.06	4.09	4.41	4.42	4.42	5.07

(continued)

Appendix A.8 (continued): Strategy Returns and its Relationship with Climate Disasters

Panel C		[1]			[1, 2]			[1, 3]			[1, 4]			[1, 5]		
Dependent variable		Low	High	High − Low	Low	High	High − Low	Low	High	High − Low	Low	High	High − Low	Low	High	High − Low
	Constant	0.0005	0.0007	0.0001	0.0011	0.0013	0.0003	0.0017	0.0020	0.0004	0.0023	0.0028	0.0005	0.0028	0.0034	0.0005
		2.65	3.22	2.66	2.84	3.34	2.61	3.05	3.52	2.64	3.26	3.75	2.79	3.39	3.84	2.61
	Climate dummy	−0.0003	−0.0003	−0.00004	−0.0006	−0.0006	−0.00002	−0.0010	−0.0011	−0.0001	−0.0016	−0.0016	0.00004	−0.0020	−0.0019	0.0001
		−0.59	−0.66	−0.34	−0.64	−0.65	−0.08	−0.75	−0.80	−0.29	−0.98	−0.94	0.12	−1.02	−0.97	0.21
	Adj. $R^2$2	−0.03%	−0.02%	−0.04%	−0.004%	−0.005%	−0.04%	0.03%	0.04%	−0.04%	0.11%	0.09%	−0.04%	0.14%	0.11%	−0.04%

Panel D		w=2			w=4			w=6			w=8		
Dependent variable		Low	High	High − Low	Low	High	High − Low	Low	High	High − Low	Low	High	High − Low
	Constant	0.0058	0.0066	0.0008	0.0120	0.0135	0.0014	0.0183	0.0202	0.0019	0.0236	0.0254	0.0019
		4.51	4.94	2.56	6.82	7.45	3.21	8.63	9.09	3.48	9.43	9.65	2.84
	Climate dummy	−0.0041	−0.0039	0.0001	−0.0091	−0.0083	0.0007	−0.0142	−0.0129	0.0013	−0.0149	−0.0116	0.0033
		−1.43	−1.35	0.21	−2.17	−1.97	0.86	−2.98	−2.69	1.14	−2.91	−2.28	2.40
	Adj. R^2	0.42%	0.36%	−0.04%	1.25%	1.00%	0.08%	2.27%	1.75%	0.19%	2.04%	1.15%	1.06%
		w=10			w=12								
Dependent variable		Low	High	High − Low	Low	High	High − Low						
	Constant	0.0283	0.0303	0.0020	0.0331	0.0360	0.0029						
		9.94	10.27	2.79	10.97	11.62	3.46						
	Climate dummy	−0.0138	−0.0097	0.0042	−0.0136	−0.0096	0.0041						
		−2.38	−1.69	2.58	−2.16	−1.56	2.39						
	Adj. R^2	1.37%	0.62%	1.32%	1.17%	0.54%	1.06%						

Note: This table presents the short- and long-run portfolio returns and the high−low strategy returns and their relationship with the climate disasters. The long−short strategy consists in buying stocks with the highest previous week's order imbalance and selling stocks with the previous week's lowest order imbalance. The sample period is January 2010 to December 2018. Panels A and B report the percentage value-weighted portfolio returns based on the previous month's market capitalization in the short and long run. Panels C and D report the short- and long-run average estimates when regressing the low, high, and high−low portfolio returns on a climate dummy, equal to one during climate disaster days and zero otherwise. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.9: Return Comovement Estimates on the Low, High and High − Low Return Portfolios and their Relationship with Climate Disasters

	CD	**Non-CD**
Panel A		
Low return comovement	1.0652	0.9942
	32.73	265.26
High return comovement	1.0151	0.9670
	30.78	188.62
High − Low return comovement	−0.1221	0.1128
	−0.80	0.93
Panel B		
Low return comovement	1.0854	1.0878
	30.02	52.88
High return comovement	1.0486	1.0577
	28.62	56.41
High − Low return comovement	−0.1417	0.0892
	−0.87	0.70

Note: This table presents the relationship between the return comovement estimates on the low, high, and high−low return portfolios during climate disasters. In particular, we sort firms into two groups each climate disaster day using the previous week's retail order imbalance. We compute the value-weighted portfolio returns based on the previous month's market capitalization. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily return comovement coefficients by using a forward-looking 90-day window to estimate the rolling regression model of Equation (5) for each of the low, high, and high−low portfolios. The dependent variable is the firm's returns, and the independent variable includes the portfolio returns. Panel A reports the value-weighted comovement coefficients based on the previous month's market capitalization for firms affected (CD) and non-affected (non-CD) by a climate disaster. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.10: Climate Disaster Return Comovement Estimates on the Climate Disaster Low, High and High − Low Return Portfolios and their Relationship with Climate Disasters

	Low			High			High − Low		
	CD	Non-CD	Difference	CD	Non-CD	Difference	CD	Non-CD	Difference
Panel A									
CD comovement	0.4800	0.4303	0.0498	0.3791	0.3855	−0.0064	0.0550	0.0368	0.0182
	14.56	20.13	1.52	11.22	16.42	−0.26	1.46	1.63	0.58
Non-CD comovement	1.0147	0.9670	0.0478	1.0654	0.9945	0.0709	−0.1354	0.1025	−0.2379
	30.72	183.01	1.47	32.79	263.12	2.22	−0.89	0.86	−2.61
Panel B									
CD comovement	0.5010	0.4983	−0.0052	0.3935	0.4003	−0.0168	0.0889	0.0867	−0.0012
	17.28	26.65	−0.18	13.39	14.75	−0.84	2.25	4.09	−0.03
Non-CD comovement	1.0483	1.0576	−0.0073	1.0860	1.0887	0.0024	−0.1550	0.0795	−0.1783
	28.59	56.70	−0.21	30.06	53.02	0.07	−0.95	0.63	−2.04

Note: This table presents the relationship between return comovement estimates of firms affected (CD) and non-affected (non-CD) by a climate disaster on their low, high, and high−low return portfolios during climate disasters. In particular, we sort firms into two groups on each climate disaster day using the previous week's retail order imbalance. Then for each group, we consider the CD and non-CD firms. We compute the value-weighted portfolio returns based on the previous month's market capitalization. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily return comovement coefficients of CD and non-CD firms by using a forward-looking 90-day window to estimate a similar rolling regression model as in Equations (6) and (7) for each of the CD and non-CD low, high, and high−low portfolios. The dependent variable is the firm's returns, and the independent variable includes the portfolio returns. Panel A reports the value-weighted CD and non-CD comovement coefficients based on the previous month's market capitalization during climate disasters for CD and non-CD firms. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.11: Order Imbalance Comovement Estimates on the Low, High and High − Low Order Imbalance Portfolios and their Relationship with Climate Disasters

	CD	**Non-CD**
Panel A		
Low imbalances comovement	0.4588	0.6607
	4.30	21.60
High imbalances comovement	0.3378	0.6316
	2.40	19.76
High − Low imbalances comovement	−0.4002	−0.4272
	−1.70	−6.36
Panel B		
Low imbalances comovement	0.6086	0.7796
	5.98	59.24
High imbalances comovement	0.4450	0.8002
	2.90	49.86
High − Low imbalances comovement	−0.5125	−0.2703
	−2.20	−5.03

Note: This table presents the relationship between the order imbalance comovement estimates on the low, high, and high−low return portfolios during climate disasters. In particular, we sort firms into two groups on each climate disaster day using the previous week's retail order imbalance. We compute equal-weighted order imbalance portfolios. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily order imbalance comovement coefficients by using a forward-looking 90-day window to estimate the rolling regression model of Equation (8) for each of the low, high, and high−low portfolios. The dependent variable is the firm's order imbalances, and the independent variable includes the retail order imbalances portfolio. Panel A reports the value-weighted comovement coefficients based on the previous month's market capitalization for firms affected (CD) and non-affected (non-CD) by a climate disaster. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.

Appendix A.12: Climate Disaster Order Imbalance Comovement Estimates on the Climate Disaster Low, High and High − Low Order Imbalance Portfolios and their Relationship with Climate Disasters

	Low			High			High − Low		
	CD	**Non-CD**	**Difference**	**CD**	**Non-CD**	**Difference**	**CD**	**Non-CD**	**Difference**
Panel A									
CD comovement	0.0805	0.0554	0.0251	0.1772	0.0322	0.1449	−0.0494	0.0054	−0.0548
	2.28	3.77	0.84	4.54	3.25	3.59	−1.77	0.84	−1.88
Non-CD comovement	0.3362	0.6298	−0.2937	0.4573	0.6607	−0.2035	−0.4146	−0.4351	0.0206
	2.38	19.72	−2.15	4.29	21.56	−1.90	−1.76	−6.43	0.08
Panel B									
CD comovement	0.1490	0.0490	0.0980	0.2550	0.0653	0.1872	−0.0695	−0.0148	−0.0547
	4.01	4.42	2.98	6.71	4.83	5.48	−2.88	−1.89	−2.35
Non-CD comovement	0.4362	0.7990	−0.3630	0.5995	0.7793	−0.1795	−0.5306	−0.2790	−0.2419
	2.84	49.92	−2.45	5.87	59.91	−1.79	−2.27	−5.13	−1.04

Note: This table presents the relationship between the order imbalance comovement estimates of firms affected (CD) and non-affected (non-CD) by a climate disaster on their low, high, and high−low order imbalance portfolios during climate disasters. In particular, we sort firms into two groups on each climate disaster day using the previous week's retail order imbalance. Then for each group, we consider the CD and non-CD firms. We compute equal-weighted order imbalance portfolios. The sample period is January 2010 to December 2018. Following Goetzmann et al. (2015), we redesign the return comovement analysis to accommodate our context (Green and Hwang, 2009; Kumar et al., 2013). Specifically, we obtain the daily order imbalance comovement coefficients of CD and non-CD firms by using a forward-looking 90-day window to estimate a similar rolling regression model as in Equations (9) and (10) for each of the CD and non-CD low, high, and high−low portfolios. The dependent variable is the firm's order imbalances, and the independent variable includes the retail order imbalances portfolio. Panel A reports the value-weighted CD and non-CD comovement coefficients based on the previous month's market capitalization during climate disasters for CD and non-CD firms. In contrast, Panel B reports the equal-weighted comovement coefficients. We adjust the standard errors using Newey-West (1987) with five lags to correct the serial correlation.