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Marinela Adriana Finta

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

SMU
SINGAPORE MANAGEMENT UNIVERSITY

SIM KEE BOON INSTITUTE FOR FINANCIAL ECONOMICS

LEE KONG CHIAN SCHOOL OF BUSINESS

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Marinela Adriana Finta[†]

[†]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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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.

Keywords: Retail Investors; Climate Disasters.

1 Introduction

Understanding investors' trading behavior matters especially given the frequent occurrence of climate disasters. Indeed, recent studies find that these events affect the stock market returns and point forward that investors' and analysts' attention and proximity to them affect their trading decisions (Bernile et al., 2021; Alok et al., 2020; Bourdeau-Brien et al., 2020; Han et al., 2020; Akbas and Subasi, 2019; Bui et al., 2019). For instance, Alok et al. (2020) show that fund managers near a climate disaster underweight the disaster stocks relative to those located further away. This evidence is in line with that in the behavioral literature in that if the effects of climate change are more prominent and close to their location, investors pay more attention to these events and, thus, may suffer less from limited attention.

While fund managers and institutional investors possess the necessary skills and strong ties with market players to accurately interpret climate disasters, or earnings announcements and allocate large amounts of resources for firm' analysis, retail investors may not. 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. Consequently, as Kelley and Tetlock (2013) underline, "...retail traders have clear incentives to trade on novel information gleaned from geographic proximity to firms...." Hence, climate disasters may provide insights into their role in stock pricing and worthy opportunities when they are near the occurrence of these events. As such, the question is - can retail investors accurately assess the implications of climate disasters for their trading decisions and evaluation of the earnings surprises? If so, can they (e.g., those closer or further away from the disaster events) obtain an additional information advantage on the future performance of stock prices and, thus, create a profitable trading strategy during climate disasters?

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. 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? Can they correctly predict future returns during these events? Or are retail traders more likely to make mistakes in their trading decisions during disasters? 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. First, investors trade less on climate disaster 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.In addition, retail buyers exhibit higher returns than sellers around climate disasters (e.g., one week before and during disasters and six months before and after them). Second, we find that retail order flows are less persistent during disasters and, in line with Kelly 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 showing that climate disasters affect it. 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 (Bohmer et al., 2021; Barrot et al., 2016; Kaniel et al., 2012; Kaniel et al., 2008; Chordia and Subrahmanyam, 2004). 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 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 expected, the comovement estimates are more substantial between firms within climate disaster counties and disaster portfolios than the non-disaster portfolios.

The remainder of the paper is organized as follows. Section 2 describes the data. In Section 3, we discuss our empirical findings. Finally, Section 4 concludes the paper.

2 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. Notably, 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

3 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 3.1. We then assess the relationship between order imbalances and short and long-run returns around climate events in Section 3.2. In Sections 3.3, 3.4, and 3.5, 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 profitable trading strategy during climate disasters. The last sections, i.e., Sections 3.6 and 3.7, investigate if retail investors' trading around climate disasters can lead to comovement in returns and order imbalances.

3.1 *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 that firms' proximity to climate disasters drives our previous findings by considering the mean retail measures of firms from inside and outside the state where a climate disaster occurs.[1]

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 located in a county that is affected versus non-affected by a disaster. The findings are consistent with those of Table 3 emphasizing the relevance of retail investors' proximity to climate disasters. In particular, during climate disasters, they trade around 30% significantly less than investors in non-affected counties. For instance, the significant mean difference between total trading volume for firms in the affected and non-affected counties is around -29000, and the buy and sell volume is usually around half of it.[2]

INSERT TABLE 4 HERE

Table 5 explores retail investors' trading activity six months before to after climate disasters. Considering the firms affected by disasters, 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 firm affected by a disaster, we compute the cross-sectional averages of retail measures and then take the

[1]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.

[2]Similar to Appendix A.1, Appendix A.2 reports the significant time-series averages of cross-sectional means for retail measures of firms (affected and non-affected by a disaster) located 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 firms affected than non-affected regardless of their headquarter location (i.e., inside or outside the climate disaster state).

time-series means for every month during the six months 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 firm affected by a climate disaster, ii) average across the events for each firm and iii) the cross-sectional mean).

Investigating Table 5, we observe that during the disaster period, the order imbalances are significantly more negative than in the six months prior (see, e.g., the month before the events) and less negative than mainly the second and fourth month after disasters. These results suggest that, usually, retail investors are substantial net sellers during and after the climate disasters. Indeed, the total trading volume gradually reduces from the sixth month until three months pre-event when it slightly rises and then significantly decreases during the disaster period. Afterward, especially in the first three months after the climate disaster, the total trading volume remains low before increasing to a comparable level as the sixth to the fourth month before the event. We observe similar patterns for the retail buy and sell volume, which is usually significantly low in the three months around climate disasters, with the lowest level during the disaster period. Once again, our findings highlight the retail investors' relatively low trading (i.e., buying and selling) during and around climate disasters.[3] Appendix A.3 confirms Table's 5 results by showing the statistically significant mean differences of order imbalances and buy and sell volume six months before and after climate disasters. This significance also holds for the buy and sell volume one month before and after the 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-affected firms, i.e., those from counties without climate disasters. Results show a relatively low trading volume solely during and in the first three months after the disasters. However, their magnitude and average differences between six months and one month before and after disasters are usually smaller than those in Appendix A.3 suggesting the importance of retail investors' proximity to disasters again.

INSERT TABLE 5 HERE

[3]As robustness, Appendix A.5 presents the average retail investors' trading activity six months before to after each climate disaster (i.e., drought, flooding, hail, hurricane, tornado, wildfire, wind, and winter weather) for firms within the climate disaster area. We note that generally, for all our events, the trading volume starts decreasing one month before the event until three months afterward when it reaches the levels before it. Also, tornados, winds, hurricanes, and floods exhibit the lowest trading volume among our events.

3.2 *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 high, medium, or low 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 average percentage returns and average order imbalances in Panels A and B, respectively, of Tables 6 and 7. That is, the former and latter tables report the average percentage returns and average retail order imbalances one week and six months before to after climate disasters for firms affected by them.

Examining Table 6, we observe significant high returns one week before and during the climate disasters for medium and high retail order imbalances portfolios within the climate disaster counties. Instead, when retail investors sell more than buy, i.e., the low tercile portfolio, returns are significantly low except during climate disasters. After the climate disasters, we find negatively significant average returns for the low, medium, and high order 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. The average statistically significant returns of the high−low portfolio also confirm the above conclusions.

INSERT TABLE 6 HERE

In the long run, i.e., six months before and after the climate disasters, Table 7 strengths Table's 6 results by documenting the significantly positive higher returns of the high order imbalances portfolio than those of both low and medium portfolios. Moreover, the high−low portfolio exhibits significant positive returns both before and after disasters, highlighting once again the substantial benefits of the retail investors when being net buyers rather than sellers.

INSERT TABLE 7 HERE

3.3 *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 0.0505. The negative b_3 coefficient suggests that the effect of past order imbalances on future order imbalances is 0.0526 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 0.0870 (i.e., 0.1396+(-0.0526)), whereas, when there are no climate disasters, it is 0.1396. In line with Boehmer et al. (2021), coefficients for the past week, month, and six months returns are highly significant, i.e., -0.7630, -0.2704, and -0.0397, 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

3.4 *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 0.36, 1.33, 1.75, and 2.47 basis points). That is, the one-week, one-month, two-month, 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., 0.0003+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. 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.[4]

INSERT TABLE 10 HERE

Finally, Table 11 investigates retail order imbalances' ability to predict the earnings surprises during climate disasters. Following Kelly 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 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 Kelly 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 Kelly 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 con-

[4] 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.

tain 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

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

Previous sections emphasize the importance of climate disasters for retail investors' trading. 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. If their selection is in the right direction, then firms with positive retail order imbalances would exhibit higher returns than those with negative imbalances. 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 firms affected and non-affected by a climate disaster. 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.[5]

Generally, in the short run, Panel A documents significant negative and positive high−low portfolio returns for the CD and non-CD firms. The negative returns suggest that 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. Instead, when buying more than selling stocks of firms outside disaster counties, even around climate disasters, investors experience highly significant and positive returns. In Panel B, we usually 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%),

[5]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.

whereas for the non-CD firms, returns are statistically significant over all horizons (e.g., two, four, six, eight and twelve week).[6] These results imply that when investors buy more than sell stocks of firms from or outside disaster counties, they achieve favorable long-term returns. [7]

INSERT TABLE 12 HERE

3.6 *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. Results show a gradually positive and significant decline in the average return comovement from the low to the

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

[7] Appendix A.8 reports the short-run, long-run, and long−short portfolio returns and their relationship with 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 of the daily Fama-MacBeth regressions where the dependent variable is each of the low, high, and high-low portfolio returns. The independent variable is the event dummy equal to one during climate disasters and zeroes otherwise. In line with Table 12, results show significantly negative returns for both low and high portfolios in the long run (e.g., over the four-week to twelve-week ahead). Climate disasters also affect the eight-, ten- and twelve-week long−short portfolio return, which is highly positively significant.

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., Tables 3 and 5), and iii) when many retail investors trade in the same direction, i.e., sell more than buying, their returns are negative and additionally, being one of the few net buyers who essentially are not following the crowd pays off, i.e., returns are highly positive (see, Table 6). Thus, 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.[8]

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. As we expect, generally, the CD and non-CD firms' returns largely comove with the CD and non-CD portfolio returns, regardless of whether the retail investors are net buyers or sellers. In addition, considering the CD firms in Panel B, the difference in average return comovement coefficients

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

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. These findings validate to some extent Table's 13 conclusion pointing towards a large comovement of CD and non-CD firms' returns with the low order imbalance portfolio return.[9]

INSERT TABLE 14 HERE

3.7 *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.[10] To do so, using a forward-looking 30-day window, we estimate the following rolling regression models:

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

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

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

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,

[9] 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.

[10] 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.

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 a large comovement between the CD and non-CD firms' order imbalances and the CD and non-CD low and high order imbalance portfolio. Nevertheless, regardless of the low or high portfolio, the difference between the CD and non-CD comovement coefficients is mostly insignificant for either CD or non-CD firms. The exception is the equal-weighted coefficients of the former firms in Panel B, which emphasize the significant greater comovement with the CD low and high portfolios. However, the comovement is stronger with the former portfolio, e.g., the CD high−low is highly negatively significant for the CD firms. This result confirms the order imbalances' persistence and highlights that once again, during climate disasters, many retail investors may similarly trade, e.g., sell more than buy stocks of firms from CD counties.

INSERT TABLE 16 HERE

4 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. Investors trade significantly less during and around disasters, especially three months after them, and they are usually net sellers. We note that in the short term, e.g., one week before and during climate disasters, retail investors who sell more than buy experience lower returns than those who either buy and sell or are buyers rather than sellers. In the long-term, i.e., six months before and after the climate disasters, retail net buyers continue to 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 higher between firms' returns from disaster counties and the climate disaster portfolio return than the non-disaster portfolio return. The order imbalance comovement presents similar patterns to the return comovement.

References

Akbas, F., and Subasi, M., 2019. Corporate news releases and the profitability of retail trades. *Working Paper.*

Alok, S., Kumar, N. and Wermers, R., 2020. Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies*, *33*(3), 1146-1183.

Barber, B.M. and Odean, T., 2008. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The review of financial studies*, *21*(2), 785-818.

Barber, B.M., Odean, T. and Zhu, N., 2009. Do retail trades move markets? *The Review of Financial Studies*, *22*(1), 151-186.

Barrot, J.N., Kaniel, R. and Sraer, D., 2016. Are retail traders compensated for providing liquidity? *Journal of Financial Economics*, *120*(1), 146-168.

Bernile, G., Bhagwat, V., Kecskés, A., and Nguyen, P. A., 2021. Are the risk attitudes of professional investors affected by personal catastrophic experiences? *Financial Management*, *50*(2), 455-486.

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

Bourdeau-Brien, M., and Kryzanowski, L., 2020. Natural disasters and risk aversion. *Journal of Economic Behavior and Organization*, *177*(9), 818-835.

Bui, D. G., Hasan, I., Lin, C. Y., and Zhang, G., 2019. Natural-disaster experience and risk-taking behaviors: Evidence from individual investor trading. *Working Paper.*

Chordia, T., and Subrahmanyam, A., 2004. Order imbalance and individual stock returns: Theory and evidence. *Journal of Financial Economics*, *72*(3), 485-518.

Green, C., and Hwang, B., 2009. Price-based return comovement. *Journal of Financial Economics*, *93*(7), 37–50.

Goetzmann, W. N., Kim, D., Kumar, A., and Wang, Q., 2015. Weather-induced mood, institutional investors, and stock returns. *The Review of Financial Studies*, *28*(1), 73-111.

Han, Y., Mao, C. X., Tan, H., and Zhang, C., 2020. Distracted analysts: Evidence from climatic disasters. *Working Paper.*

Kaniel, R., Liu, S., Saar, G. and Titman, S., 2012. Individual investor trading and return patterns around earnings announcements. *The Journal of Finance*, *67*(2), 639-680.

Kaniel, R., Saar, G., and Titman, S., 2008. Individual investor trading and stock returns. *The Journal of finance*, *63*(1), 273-310.

Kelley, E. K., and Tetlock, P. C., 2013. How wise are crowds? Insights from retail orders and stock returns. *The Journal of Finance*, *68*(3), 1229-1265.

Kumar, A., Page, J. K., and Spalt, O. G., 2013. Investor sentiment and return comovements: Evidence from stock splits and headquarters changes. *Review of Finance*, *17*(3), 921-953.

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 disasters	Non-climate disasters	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

	Climate disasters	Non-climate disasters	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 and non-affected by them. In particular, we calculate the cross-sectional mean for each retail measure during climate disaster days for each firm affected and non-affected by a disaster 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

	m − 6	m − 5	m − 4	m − 3	m − 2	m − 1	0	m + 1	m + 2	m + 3	m + 4	m + 5	m + 6
Order imbalances	−0.028	−0.034	−0.034	−0.030	−0.034	−0.029	−0.035	−0.032	−0.050	−0.026	−0.042	−0.033	−0.025
	−9.05	−12.40	−13.54	−10.84	−12.29	−10.56	−5.95	−11.48	−19.98	−11.96	−21.90	−14.50	−13.33
Buy volume	42249	38367	38025	35595	36178	37277	33683	33936	33596	34754	35915	38505	38534
	76.58	70.13	72.50	69.73	89.91	90.69	14.37	80.24	81.77	94.79	69.82	50.29	75.41
Sell volume	43058	38890	39094	36020	36551	36977	33437	34036	34705	34167	36951	37225	38578
	77.51	72.44	77.35	80.35	106.82	91.41	14.62	93.35	80.44	86.38	53.71	63.34	70.04
Total volume	85306	77257	77120	71615	72728	74254	67120	67972	68301	68921	72866	75730	77112
	83.78	73.73	80.32	80.08	106.67	98.28	14.55	88.87	85.22	92.79	62.60	66.83	82.13

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, six months before to after climate disasters for firms affected by them. We calculate the cross-sectional mean for each retail measure around climate disaster days for each firm affected by a disaster 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 firm affected by a climate disaster 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	−0.184	−0.108	−0.052	−0.010	−0.093	0.210	−0.201	−0.262	−0.310	−0.322	−0.297
	−2.60	−2.90	−2.90	−0.42	−1.13	4.97	−2.10	−14.86	−11.05	−12.78	−16.04
Medium	0.065	0.177	0.202	0.360	0.447	0.261	−0.396	−0.416	−0.289	−0.286	−0.193
	0.60	2.65	2.63	14.41	2.16	5.78	−4.62	−74.55	−5.47	−7.06	−2.46
High	−0.032	0.131	0.164	0.209	0.059	0.233	−0.215	−0.131	−0.114	−0.165	−0.087
	−0.28	4.60	6.17	4.84	0.68	4.25	−2.64	−5.37	−5.52	−6.55	−2.14
High−Low	0.152	0.239	0.216	0.219	0.153	0.022	−0.015	0.131	0.196	0.157	0.209
	3.14	14.04	17.64	11.46	1.18	0.62	0.11	3.11	4.11	5.08	5.23
Panel B: Order imbalances											
Low	−0.467	−0.465	−0.465	−0.470	−0.476	−0.323	−0.443	−0.455	−0.454	−0.456	−0.455
Medium	−0.021	−0.021	−0.021	−0.021	−0.024	−0.023	−0.020	−0.027	−0.024	−0.021	−0.021
High	0.400	0.400	0.399	0.391	0.379	0.239	0.411	0.403	0.403	0.405	0.405

This table presents the average percentage returns and average retail order imbalances one week before to after climate disasters for firms affected by them. Using retail order imbalances, we sort firms affected by a disaster 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 firm affected by a climate disaster 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

	m − 6	m − 5	m − 4	m − 3	m − 2	m − 1	0	m + 1	m + 2	m + 3	m + 4	m + 5	m + 6
Panel A: Returns													
Low	−0.160	−0.040	−0.013	−0.103	−0.018	−0.112	0.210	−0.155	−0.026	−0.019	−0.089	−0.021	0.029
	−3.90	−0.72	−0.33	−1.51	−0.52	−2.35	4.97	−2.47	−0.39	−0.61	−1.51	−0.50	0.46
Medium	−0.023	0.121	0.126	0.025	0.115	0.059	0.261	−0.009	0.061	0.218	0.119	0.120	0.200
	−0.38	1.84	3.59	0.51	2.26	1.09	5.78	−0.13	1.09	7.06	1.70	2.94	3.61
High	0.051	0.203	0.214	0.097	0.205	0.171	0.233	0.064	0.128	0.226	0.137	0.198	0.264
	1.10	3.87	4.89	1.41	5.18	3.49	4.25	1.29	2.81	5.55	1.99	4.99	5.74
High−Low	0.211	0.243	0.227	0.200	0.223	0.284	0.022	0.219	0.153	0.245	0.226	0.219	0.235
	8.25	9.73	10.90	6.85	13.42	7.12	0.62	5.84	3.69	8.86	7.30	11.24	6.76
Panel B: Order imbalances													
Low	−0.461	−0.466	−0.465	−0.473	−0.469	−0.458	−0.323	−0.467	−0.488	−0.457	−0.473	−0.463	−0.447
Medium	−0.023	−0.030	−0.026	−0.025	−0.025	−0.023	−0.023	−0.028	−0.042	−0.020	−0.035	−0.028	−0.021
High	0.395	0.393	0.400	0.394	0.390	0.395	0.239	0.398	0.379	0.397	0.381	0.390	0.391

Note: This table presents the average percentage returns and retail order imbalances six months before and after climate disasters for firms affected by them. Using retail order imbalances, we sort firms affected by a disaster 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 firm affected by a climate disaster 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	−0.3983
	−7.81
Event dummy	0.0505
	1.78
Order imbalances (w−1)	0.1396
	25.79
Order imbalances (w−1)*Event dummy	−0.0526
	−1.92
Returns (w−1)	−0.7630
	−14.02
Returns (m−1)	−0.2704
	−11.86
Returns (m−7, m−2)	−0.0397
	−4.38
Turnover	0.0207
	1.75
Volatility	0.6081
	3.28
Size	0.0112
	4.90
B/M	−0.0130
	−4.52
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 is a dummy equal to one during climate disasters and zeroes 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	0.0036	0.0133	0.0175	0.0247
	2.40	3.00	2.13	2.08
Returns	−0.0239	−0.2008	−0.1895	−0.1428
	−0.89	−2.53	−1.28	−0.67
Turnover	−0.0174	−0.0813	−0.1999	−0.2202
	−1.39	−2.20	−2.91	−2.21
Volatility	−0.1870	0.2261	1.5794	1.0015
	−1.40	0.57	2.16	0.94
Size	−0.0097	−0.0468	−0.0589	−0.1120
	−2.45	−3.98	−2.69	−3.53
B/M	0.0103	0.0197	0.0163	0.0277
	2.68	1.74	0.77	0.91
$\mathbf{R}^2$	58.75%	64.84%	66.44%	66.12%

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	−0.0017	−0.0026	0.0053	0.0081	0.0038
	1.28	0.81	0.71	0.47	0.29	0.37	−0.33	−0.55	1.19	1.54	0.73
Event dummy	−0.0007	−0.0012	−0.0017	−0.0021	−0.0025	−0.0003	−0.0021	−0.0028	0.0014	0.0008	0.0004
	−1.34	−1.31	−1.41	−1.51	−1.65	−0.22	−1.55	−2.40	0.80	0.43	0.26
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
	6.12	6.81	7.49	7.90	7.54	3.89	3.47	2.88	0.80	1.75	1.59
Order imbalances (w−1)*Event dummy	−0.0001	−0.0002	−0.0003	0.0000	−0.0004	0.0012	0.0007	0.0014	−0.0040	0.0001	0.0008
	−0.15	−0.16	−0.19	−0.01	−0.23	0.81	0.55	1.07	−1.97	0.05	0.51
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
	5.50	4.80	4.90	4.80	4.78	4.16	3.13	2.40	0.64	2.45	2.22
Order imbalances (m−1)*Event dummy	−0.0003	−0.0007	−0.0009	−0.0012	−0.0015	−0.0003	0.0004	−0.0012	0.0008	0.0001	0.0003
	−1.38	−1.92	−1.74	−1.87	−2.09	−0.41	0.55	−2.15	1.09	0.20	0.47
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
	1.01	1.34	1.36	1.00	0.63	−0.30	−1.04	−0.14	−0.61	−1.57	−1.11
Order imbalances (m−7, m−2)*Event dummy	0.0000	0.0002	0.0002	0.0003	0.0003	−0.0001	−0.0001	−0.0001	0.0001	0.0002	0.0003
	0.66	1.46	1.78	1.80	1.75	−0.25	−0.78	−0.33	0.63	0.92	1.42
Returns (w−1)	−0.0177	−0.0241	−0.0276	−0.0291	−0.0295	−0.0014	−0.0107	0.0001	0.0073	0.0012	−0.0009
	−6.14	−6.84	−6.40	−5.71	−4.79	−0.22	−2.38	0.03	1.47	0.26	−0.22
Returns (m−1)	−0.0016	−0.0028	−0.0036	−0.0034	−0.0034	−0.0025	−0.0035	0.0007	−0.0006	0.0024	0.0043
	−1.57	−1.46	−1.32	−1.02	−0.88	−0.71	−0.88	0.18	−0.18	0.76	1.37
Returns (m−7, m−2)	0.0004	0.0009	0.0014	0.0018	0.0024	0.0015	0.0000	0.0006	0.0005	0.0010	0.0004
	1.26	1.68	1.84	2.04	2.41	1.47	0.02	0.47	0.37	0.81	0.34
Turnover	−0.0003	−0.0008	−0.0015	−0.0024	−0.0030	−0.0003	−0.0034	−0.0034	−0.0002	−0.0004	−0.0028
	−0.78	−1.00	−1.31	−1.60	−1.66	−0.13	−1.66	−2.09	−0.08	−0.23	−1.40
Volatility	0.0003	0.0031	0.0046	0.0029	0.0042	0.0155	0.0243	−0.0092	−0.0332	−0.0070	−0.0084
	0.03	0.21	0.22	0.11	0.14	0.58	0.70	−0.28	−1.18	−0.27	−0.29
Size	−0.00005	−0.00005	−0.0001	−0.0001	−0.00001	0.00003	0.0001	0.0001	−0.0002	−0.0002	0.0000
	−0.74	−0.40	−0.44	−0.28	−0.05	0.12	0.35	0.38	−0.72	−0.65	−0.15
B/M	0.00001	0.00005	0.0001	0.0001	0.00003	−0.0005	−0.00002	0.0003	0.0005	0.0001	0.0006
	0.14	0.25	0.30	0.19	0.07	−1.36	−0.04	0.72	1.35	0.37	1.63
Adj. R^2	3.63%	3.90%	4.03%	4.06%	4.02%	3.96%	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 is a dummy equal to one during climate disasters and zeroes 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 is a dummy equal to one during climate disasters and zeroes 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 Kelly 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	2.41	0.41	2.57	0.06	2.72	0.28	2.80	0.66	2.93
High	−0.069	−0.001	−0.144	0.008	−0.315	−0.051	−0.314	−0.041	−0.198	0.014
	−0.94	3.03	−0.93	3.17	−1.32	3.26	−1.06	3.42	−0.62	3.51
High−Low	−0.115	0.011	−0.199	0.020	−0.326	0.018	−0.382	0.036	−0.367	0.039
	−1.57	2.83	−1.62	2.92	−1.92	2.81	−1.71	3.20	−1.45	3.03

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	3.87	0.90	5.57	−0.13	7.04	−0.50	8.35	0.11	9.37	0.45	10.79
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	4.39	0.51	6.39	0.56	7.85	1.43	9.26	2.53	10.40	2.66	12.13
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	2.98	−0.12	4.04	0.70	4.32	1.65	4.39	1.90	4.43	1.88	4.97

Note: This table presents the short and long-run portfolio returns and the high−low strategy returns during climate disasters for firms affected and non-affected 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. 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 affected and non−affected by a climate disaster 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 affected and non−affected 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. 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 affected and non-affected by a climate disaster 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 affected and non-affected 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 Disasters and Non-Climate Disasters Days considering the State

	Climate disasters	Non climate disasters	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, 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

	Climate disasters	Non climate disasters	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, and their difference, during climate disaster days for firms affected and non-affected by them. 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 cross-sectional mean for each retail measure during climate disaster days for each firm affected and non-affected by a disaster 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: Six months before and after climate disasters			
Order imbalances	−0.032	−0.035	0.003
	−27.78	−28.94	1.84
Buy volume	37948	35873	2075
	137.41	131.19	5.34
Sell volume	38432	35944	2488
	135.65	139.38	6.49
Total volume	76380	71817	4563
	141.22	144.22	6.21
Panel B: One month before and after climate disasters			
Order imbalances	−0.029	−0.032	0.002
	−10.56	−11.48	0.64
Buy volume	37277	33936	3341
	90.69	80.24	5.67
Sell volume	36977	34036	2941
	91.41	93.35	5.40
Total volume	74254	67972	6282
	98.28	88.87	5.84

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy sell volume. Panels A and B report these averages and their difference six months before and after climate disasters for firms affected by them and one month before and after, respectively. We calculate the cross-sectional mean for each retail measure around climate disaster days for each firm affected by a disaster 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 around Climate Disasters considering the Non-affected Firms

Panel A: Six months before to after climate disasters

	m − 6	m − 5	m − 4	m − 3	m − 2	m − 1	0	m + 1	m + 2	m + 3	m + 4	m + 5	m + 6
Order imbalances	−0.029	−0.033	−0.029	−0.030	−0.035	−0.032	−0.030	−0.037	−0.049	−0.023	−0.040	−0.031	−0.025
	−14.50	−19.27	−13.84	−19.91	−19.91	−25.96	−138.57	−20.98	−30.46	−13.19	−26.38	−25.95	−17.12
Buy volume	44701	43118	43334	43312	44554	45254	40252	41603	41386	43222	42324	42390	43647
	159.91	166.13	225.41	212.69	119.87	120.60	331.83	158.55	107.87	202.79	228.10	221.76	278.19
Sell volume	44379	42865	43484	43524	45214	44608	40084	42135	42671	42715	42928	42507	43953
	140.27	150.64	150.12	163.58	97.10	118.32	334.38	147.20	102.36	201.81	186.60	235.68	185.50
Total volume	89080	85983	86818	86837	89768	89863	80336	83738	84056	85937	85253	84897	87599
	153.96	167.14	204.69	201.80	111.95	123.40	334.49	162.61	107.37	223.23	215.36	248.06	233.13

	Before	After	Difference
Panel B: Six months before and after climate disasters			
Order imbalances	−0.031	−0.034	0.003
	−43.30	−33.75	2.47
Buy volume	44046	42429	1617
	321.11	349.75	8.83
Sell volume	44012	42818	1194
	286.82	357.86	6.14
Total volume	88058	85247	2811
	318.54	375.50	7.86
Panel C: One month before and after climate disasters			
Order imbalances	−0.032	−0.037	0.006
	−25.96	−20.98	2.60
Buy volume	45254	41603	3652
	120.60	158.55	7.98
Sell volume	44608	42135	2473
	118.32	147.20	5.22
Total volume	89863	83738	6125
	123.40	162.61	6.87

Note: This table presents the time-series averages of the cross-sectional mean for retail investors' trading activity, i.e., order imbalances, buy sell volume. Panel A reports the averages for the six months before to after climate disasters for firms affected by them. Panels B and C report the averages and their difference six months before and after climate disasters and one month before and after, respectively. We calculate the cross-sectional mean for each retail measure around climate disaster days for each firm affected by a disaster 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 firm affected by a climate disaster 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

	m − 6	m − 5	m − 4	m − 3	m − 2	m − 1	0	m + 1	m + 2	m + 3	m + 4	m + 5	m + 6
Panel A: Drought													
Order imbalances	−0.004	−0.018	−0.063	−0.027	−0.050	−0.026	−0.035	−0.003	−0.026	−0.037	−0.030	−0.041	−0.043
	−0.40	−1.58	−5.51	−2.47	−5.34	−2.15	−1.99	−0.32	−3.16	−3.42	−2.92	−4.15	−4.99
Buy volume	36727	35675	43193	37878	50024	40928	44411	41499	48808	40772	43713	35318	39084
	25.25	22.66	16.52	30.14	16.85	20.09	2.77	29.81	17.64	29.26	28.02	41.54	20.48
Sell volume	33928	34340	40832	35107	46614	41002	42325	40100	47096	38059	45521	36244	37788
	38.60	18.43	16.70	27.12	16.60	20.61	2.90	24.07	12.75	31.62	25.89	35.18	18.32
Total volume	70656	70015	84026	72984	96637	81931	86736	81598	95904	78831	89234	71562	76872
	44.69	21.37	17.20	32.07	17.27	22.21	2.83	28.71	15.00	32.67	29.29	44.05	20.15
Panel B: Flooding													
Order imbalances	-0.022	-0.032	-0.034	−0.035	−0.032	−0.024	−0.030	−0.031	−0.040	−0.031	−0.052	−0.034	−0.020
	−7.74	−8.98	−12.29	−10.84	−10.73	−7.48	−3.92	−8.25	−15.14	−11.77	−14.85	−9.75	−8.38
Buy volume	53215	44449	44774	39243	39506	43887	37358	37257	37467	36692	35874	38249	41309
	42.54	48.36	51.55	59.23	72.03	46.46	10.94	58.86	84.64	84.37	61.14	114.75	86.95
Sell volume	56694	47405	46978	40018	39536	42954	35953	36681	37940	36687	37752	38872	41660
	33.79	46.71	46.03	70.05	94.23	44.04	11.30	90.54	59.32	85.08	86.66	77.50	78.61
Total volume	109909	91854	91751	79261	79042	86841	73311	73938	75406	73379	73627	77122	82969
	42.08	48.41	52.08	72.64	92.28	47.26	11.16	74.42	75.37	90.07	76.48	102.88	88.44
Panel C: Hail													
Order imbalances	-0.029	-0.025	-0.021	−0.035	−0.030	−0.023	−0.022	−0.022	−0.021	−0.038	−0.033	−0.039	−0.046
	−4.02	−5.69	−4.72	−5.41	−5.62	−3.99	−1.30	−3.67	−3.36	−6.55	−5.06	−7.13	−9.24
Buy volume	48231	51816	45559	42022	39973	43288	37848	47118	45122	40876	42626	46385	46060
	27.43	48.77	53.46	47.73	50.82	51.50	6.54	58.53	33.68	40.75	50.69	30.37	50.08
Sell volume	47436	48005	46409	42370	41309	42083	40445	46228	45039	40545	42884	47766	46478
	31.73	47.78	49.64	40.65	38.79	52.28	5.94	61.51	34.12	44.11	43.57	33.20	44.65
Total volume	95667	99821	91968	84392	81282	85371	78294	93346	90161	81421	85510	94151	92538
	30.11	50.94	56.31	48.64	54.04	62.07	6.28	66.53	36.59	47.03	49.33	32.77	52.54
Panel D: Hurricane/Tropical Storm													
Order imbalances	-0.022	-0.021	-0.018	−0.014	−0.015	−0.006	−0.019	−0.014	−0.027	−0.027	−0.021	−0.014	−0.014
	−3.34	−3.02	−4.38	−2.87	−2.94	−0.90	−1.23	−2.81	−3.80	−5.52	−5.10	−2.72	−2.99
Buy volume	28070	31426	28913	33622	29693	28840	34430	34028	27177	25901	31257	33746	30904
	33.13	34.16	30.55	19.08	24.86	38.68	7.03	17.25	36.89	44.01	21.79	30.21	30.85
Sell volume	27562	31714	27533	32608	29598	29229	35506	33920	28127	27235	31541	34370	31118
	35.19	29.88	32.90	23.39	31.42	36.37	7.03	19.17	33.20	54.57	22.92	32.19	31.58
Total volume	55632	63140	56446	66231	59291	58070	69936	67948	55304	53136	62798	68116	62022
	34.65	32.27	32.59	21.23	28.14	38.39	7.08	18.27	35.66	50.22	22.49	31.58	31.74
Panel E: Tornado													
Order imbalances	-0.042	-0.043	-0.037	−0.017	−0.040	−0.045	−0.042	−0.045	−0.050	−0.038	−0.023	−0.031	−0.036
	−6.75	−8.78	−6.07	−3.71	−6.78	−8.61	−2.40	−7.36	−9.54	−5.36	−5.54	−5.88	−6.89
Buy volume	37568	38121	39120	40167	37261	34944	30173	29495	31853	35032	40047	48777	41649
	35.04	24.16	33.03	64.99	51.99	69.97	6.88	47.59	33.59	37.79	17.87	12.26	18.23
Sell volume	38679	37619	40264	39404	37440	36499	30261	32123	31968	35104	40771	39833	39597
	40.46	35.63	39.94	75.12	68.86	52.01	6.81	45.76	48.43	36.41	11.99	20.00	20.30
Total volume	76247	75740	79385	79570	74701	71443	60434	61618	63821	70136	80818	88610	81246
	39.54	30.45	38.71	80.62	68.40	67.00	7.04	55.99	42.55	39.65	14.75	18.49	23.35

(continued)

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

	m − 6	m − 5	m − 4	m − 3	m − 2	m − 1	0	m + 1	m + 2	m + 3	m + 4	m + 5	m + 6
Panel F: Wildfires													
Order imbalances	0.004	0.002	−0.013	0.002	0.004	−0.011	0.000	−0.023	0.012	−0.001	0.028	0.008	−0.015
	0.41	0.29	−1.14	0.16	0.33	−1.07	0.01	−1.99	0.48	−0.04	1.32	0.36	−0.55
Buy volume	49196	42681	40847	47435	65946	52083	39587	48162	40072	33101	28179	33545	20662
	13.81	12.26	9.67	8.92	9.83	17.66	3.23	14.54	14.58	7.81	9.66	4.18	12.31
Sell volume	45380	40848	40941	42847	62547	51739	43357	48805	42587	30170	25897	33557	21128
	14.18	15.53	10.61	9.95	9.49	15.78	3.18	22.85	11.14	9.95	14.11	4.76	13.08
Total volume	94576	83529	81788	90282	128493	103822	82944	96967	82659	63271	54076	67102	41790
	14.14	13.76	10.19	9.46	9.72	16.96	3.21	18.52	13.54	8.92	11.76	4.47	13.17
Panel G: Wind													
Order imbalances	-0.049	-0.054	-0.045	-0.050	−0.056	−0.050	−0.046	−0.046	−0.095	0.002	−0.041	−0.037	−0.025
	−5.44	−7.70	−5.26	−7.45	−7.54	−8.85	−3.37	−6.25	−10.90	0.28	−6.67	−6.03	−5.70
Buy volume	31602	30098	29946	30239	33377	34286	33220	30455	33107	37559	37891	36956	36172
	45.14	32.40	60.50	44.47	32.88	40.76	6.54	28.92	22.19	47.17	51.36	36.09	29.64
Sell volume	33150	30491	30798	32828	35796	34471	31903	32445	36767	35144	38151	37453	38359
	32.73	37.69	37.94	35.44	25.52	43.46	7.34	26.14	27.20	43.27	45.71	37.23	26.87
Total volume	64752	60589	60744	63068	69174	68758	65123	62900	69874	72704	76042	74410	74531
	40.14	36.24	53.09	40.72	29.35	42.51	6.97	28.34	25.06	48.75	50.62	37.78	28.58
Panel H: Winter Weather													
Order imbalances						-0.049	-0.052	-0.026	-0.026	-0.036	−0.052	−0.028	−0.045
						−2.94	−1.74	−3.02	−2.32	−4.94	−5.74	−2.50	−3.45
Buy volume						17491	25081	24372	25847	31647	31915	25429	19703
						6.33	3.26	25.91	22.64	23.97	17.54	15.30	26.18
Sell volume						17797	24452	21994	23493	32418	32472	24035	20996
						7.06	3.33	42.25	28.00	26.62	24.23	22.44	22.17
Total volume						35288	49534	46366	49341	64065	64387	49464	40699
						6.71	3.30	37.18	26.51	26.88	21.22	18.74	26.16

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, six months 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 for each firm affected by a disaster 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 firm affected by a climate disaster 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	0.0018	0.0013	0.0008	0.0027	−0.0002	−0.0027	0.0045	0.0088	0.0040
	1.07	0.70	0.61	0.33	0.18	0.57	−0.04	−0.58	1.03	1.76	0.79
Event dummy	−0.0005	−0.0009	−0.0012	−0.0019	−0.0016	0.0005	−0.0014	−0.0014	0.0015	0.0001	0.0012
	−1.15	−1.44	−1.35	−1.82	−1.31	0.36	−1.14	−1.14	1.16	0.09	0.83
Order imbalances (m−1)	0.0001	0.0002	0.0003	0.0003	0.0004	0.0003	0.0003	0.0002	0.0000	0.0001	0.0001
	8.96	9.00	9.04	8.87	8.63	5.95	5.44	3.50	0.44	1.64	2.53
Order imbalances (m-1)*Event dummy	-0.0003	-0.0006	−0.0010	−0.0011	−0.00146	−0.0005	0.0001	−0.0006	0.0000	0.0018	0.0004
	−1.68	−2.06	−2.41	−2.28	−2.62	−0.95	0.20	−1.17	0.00	2.30	0.66
Returns (w−1)	−0.0189	−0.0249	−0.0287	−0.0300	−0.0307	−0.0025	−0.0109	−0.0004	0.0058	−0.0007	−0.0024
	−6.73	−7.06	−6.53	−5.70	−4.94	−0.40	−2.49	−0.09	1.22	−0.15	−0.61
Returns (m−1)	−0.0014	−0.0023	−0.0029	−0.0028	−0.0027	−0.0020	−0.0036	0.0004	−0.0008	0.0024	0.0041
	−1.37	−1.25	−1.12	−0.89	−0.74	−0.57	−0.92	0.11	−0.28	0.79	1.32
Returns (m−7, m−2)	0.0004	0.0009	0.0013	0.0018	0.0025	0.0012	−0.0001	0.0006	0.0001	0.0013	0.0003
	1.28	1.77	1.88	2.11	2.46	1.26	−0.04	0.49	0.11	1.10	0.27
Turnover	−0.0004	−0.0008	−0.0014	−0.0022	−0.0028	−0.0009	−0.0034	−0.0034	−0.0007	−0.0002	−0.0031
	−0.97	−1.00	−1.18	−1.47	−1.54	−0.44	−1.74	−2.06	−0.38	−0.13	−1.57
Volatility	−0.0006	0.0016	0.0023	0.0029	0.0039	0.0177	0.0217	−0.0123	−0.0352	−0.0074	−0.0038
	−0.08	0.11	0.12	0.12	0.14	0.71	0.67	−0.39	−1.33	−0.30	−0.14
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	−0.44	−0.44	−0.22	0.00	−0.08	0.10	0.51	−0.53	−0.74	−0.13
B/M	0.0001	0.0001	0.0001	0.0001	0.0001	−0.0005	−0.00007	0.0003	0.0006	0.0002	0.0006
	0.65	0.51	0.50	0.37	0.25	−1.37	−0.17	0.76	1.48	0.48	1.83
Adj. R^2	3.62%	3.91%	4.03%	4.03%	3.96%	3.84%	3.68%	3.22%	3.10%	2.91%	3.07%

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 is equal to one during climate disasters and zeroes 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 and non-affected 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. 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	0.045	0.091	0.138	0.182	0.227	
	2.40	2.56	2.71	2.79	2.91	
High	0.059	0.117	0.174	0.232	0.283	
	3.04	3.18	3.26	3.42	3.51	
High − Low	0.014	0.026	0.035	0.050	0.057	
	2.89	3.00	2.88	3.28	3.12	
Panel B: Long run strategy						
	w=2	**w=4**	**w=6**	**w=8**	**w=10**	**w=12**
Low	0.465	0.955	1.434	1.904	2.432	3.010
	3.86	5.57	7.04	8.34	9.37	10.78
High	0.548	1.119	1.656	2.179	2.754	3.408
	4.40	6.40	7.87	9.26	10.40	12.13
High − Low	0.083	0.164	0.222	0.276	0.321	0.398
	3.06	4.09	4.37	4.44	4.47	5.02

(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
	Event dummy	−0.0003	−0.0003	−0.00004	−0.0006	−0.0006	−0.00001	−0.0010	-0.0011	-0.0001	-0.0016	−0.0016	0.00004	−0.0020	−0.0019	0.0001
		-0.63	-0.70	-0.33	−0.66	−0.67	−0.07	−0.78	−0.82	−0.30	−1.00	−0.96	0.11	−1.05	-1.00	0.20
	Adj. R2	−0.02%	−0.02%	−0.04%	−0.001%	−0.003%	−0.04%	0.03%	0.04%	−0.04%	0.11%	0.09%	−0.04%	0.15%	0.12%	−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	0.0232	0.0251	0.0019
		4.51	4.94	2.56	6.82	7.45	3.21	8.63	9.09	3.48	9.31	9.53	2.93
	Event dummy	−0.0041	−0.0040	0.0001	−0.0092	−0.0085	0.0007	−0.0150	−0.0138	0.0012	−0.0159	−0.0127	0.0032
		-1.45	-1.37	0.22	-2.21	-2.00	0.86	−3.17	−2.89	1.10	−3.11	−2.51	2.29
	Adj. R2	0.44%	0.38%	−0.04%	1.28%	1.03%	0.07%	2.55%	2.00%	0.18%	2.33%	1.38%	0.97%

		w=10			w=12		
Dependent variable		**Low**	**High**	**High − Low**	**Low**	**High**	**High − Low**
	Constant	0.0284	0.0305	0.0021	0.0343	0.0371	0.0029
		9.94	10.29	2.88	11.36	11.99	3.42
	Event dummy	-0.0153	-0.0112	0.0041	-0.0155	-0.0114	0.0041
		−2.65	−1.97	2.50	−2.43	−1.85	2.38
	Adj. R2	1.70%	0.86%	1.26%	1.53%	0.79%	1.07%

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 of the daily Fama-MacBeth regressions. The dependent variable is each of the low, high, and high−low portfolio returns, and the independent variable includes the event dummy, equal to one during climate disasters 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. 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 affected and non-affected by a climate disaster 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 affected and non-affected 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 firms affected (CD) and non-affected (non-CD) by a climate disaster. 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 affected and non-affected by a climate disaster 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 affected and non-affected 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.