Does Climate Change Affect Retail Investors? Your Opinion Matters*

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Abstract

We examine how beliefs and concerns about climate change influence retail investment behavior. Using a decade of county-level data on public opinions regarding global warming across the United States, we construct a novel firm-level measure capturing retail investors' climate change opinions. We find that, following the disclosure of firm-level climate risk incidents, firms with retail investor bases that hold pro-climate-change opinions experience a significant decline in retail net demand, evident in both retail investors' marketable orders from TAQ and individual security positions from Robinhood Markets. Such effect is driven by egoistic and altruistic opinions, support for renewable energy, and endorsement of government and school initiatives. In contrast, no similar effect is observed for other environmental or social (ES) risk incidents that are not directly linked to climate change. This effect is more pronounced for firms with characteristics associated with investor local bias and is not driven by demographics or political leanings of retail investors. Our findings suggest that retail investors integrate their opinions about climate change into stock investment and risk management decisions.

JEL Classifications: G12, G41, G51

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1 Introduction

The last decade has witnessed substantial growth in sustainable investment. To understand the asset pricing implications of sustainable investing, a growing theoretical literature assumes that "green taste" or preference is important in investors' decision-making (e.g., Pedersen, Fitzgibbons, and Pomorski, 2021; Goldstein, Kopytov, Shen, and Xiang, 2022; Pástor, Stambaugh, and Taylor, 2021, 2022; Zerbib, 2022). Empirical studies on "green" or prosocial taste have predominantly concentrated on asset prices and costs of capital (e.g., Hong and Kacperczyk, 2009; Chava, 2014; Barber, Morse, and Yasuda, 2021). However, evidence on how these preferences specifically influence retail investors remains limited, with most insights derived from a handful of short-term experimental or field studies (e.g., Riedl and Smeets, 2017; Heeb, Kölbel, Paetzold, and Zeisberger, 2023; Giglio, Maggiori, Stroebel, Tan, Utkus, and Xu, 2024).

Meanwhile, there have been heated social and political debates surrounding issues of environmental, social, and governance (ESG), including climate change. Public backlash against ESG-related initiatives has intensified since 2019. Among investors, opinions on climate change risk and ESG investing vary significantly across the country and globally. For instance, since 2019, Illinois public funds have claimed to consider materially relevant sustainability factors, whereas in 2023, new Florida law prohibits the consideration of ESG factors when investing the state's funds. Amid a growing wave of anti-climate sentiment, both Main street and Wall Street have faced increasing criticism of ESG investing strategies. In today's context of a divided U.S. society, it has become increasingly critical to understand how such polarization in investor opinions on sustainability and climate change influences investment decisions and risk management.

Through the lens of climate change risk, we examine this important question by connecting retail investor opinions to their trading behavior using long-term archival data in the United States. We conjecture that retail investors' decision-making regarding climate risk is affected by their opinions of climate change: Do they believe in it? Are they concerned about its impact? We specifically explore to which extent such heterogeneous beliefs and concerns influence retail investors' trading decisions following the revelation of firm-specific climate risk incidents.

Identifying firm-level retail investors' opinion on climate change issues is empirically challenging. We start by capturing local climate-change opinions using annual county-level data from the Yale Climate Opinion Map (YCOM). The YCOM is derived from the large national survey "Climate Change in the American Mind", which

has been conducted twice a year since 2014.[1] This dataset is widely recognized in environmental economics and policy research and has been increasingly applied in climate finance related studies (e.g., Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020; Addoum, Ng, and Ortiz-Bobea, 2023; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2023). We focus on the responses in each continental US county to two key questions: "Do you think global warming is happening?" and "How concerned are you about global warming?". Based on the survey design, the first question is to measure "belief" in climate change, and the second one is to measure "risk perception" of climate change.

Next, we follow the assumption of local bias in retail investment (Hirshleifer, Peng, and Wang, 2024) to link the YCOM data to firms through their geographic footprints. In the context of stock market, extensive evidence reveals that investors, especially retail investors, tend to favor local firms and are more attentive to news related to them. This bias is more pronounced for smaller firms or those with regional operations (Coval and Moskowitz, 1999).[2] This suggests that firms, especially smaller or geographically concentrated ones, are reliant on local investors, and climate risk incidents involving these firms may first capture the attention of their local investor base. To operationalize this, we treat retail investors from a firm's headquarter and top operating locations as representative of the firm's retail investor base. The county-level climate change opinion data is then combined with the SEC 8-K filing for historical headquarters information and the National Establishment Time-Series (NETS) database for firms' annual footprints layout.

Additionally, we account for substantial regional variation in stock market participation (Hong, Kubik, and Stein, 2004), which affects the representativeness of local investors. Following Lin (2020) with the SOI (Statistics of Income) data from the IRS, we apply the stock market participation measure to weight local climate-change opinions. This approach allows us to finally construct a time-varying measure of climate-change opinions for retail investors at the firm level, capturing the views of the representative retail investor base for each firm.

Our analyses also draw on three additional key databases. To identify negative ESG events, we utilize the RepRisk database which tracks news incidents of firms. We focus specifically on climate risk incidents, identified based on detailed descriptions provided in the database. These include negative news related to greenhouse gas

[1] The survey with state and national level outcomes started even earlier in 2008.

[2] See more evidence of the local bias of stock investment in Grinblatt and Keloharju (2001); Benartzi (2001); Ivković and Weisbenner (2005); Chi and Shanthikumar (2017); Branikas, Hong, and Xu (2020), etc.

(GHG) emissions and pollution, coal-fired power usage, and various drilling activities. To identify retail trades, we employ the algorithm developed by Boehmer, Jones, Zhang, and Zhang (2021) (BJZZ) and Barber, Huang, Jorion, Odean, and Schwarz (2024) using trade-level TAQ data, and we also apply data from Robinhood Markets Inc. to construct alternative measures of retail investor trading activities.

Applying the final matched sample of TAQ retail trading from 2014 to 2023, we first attempt to understand how an average retail investor reacts following climate risk events. Previous research offers mixed evidence on whether retail investors respond to ES-related signals (e.g., Choi, Gao, and Jiang, 2020; Li, Watts, and Zhu, 2024; Moss, Naughton, and Wang, 2024). Without considering variations in climate-change opinions, we find no significant change in an average retail investor's trading after a negative firm-level climate incident.

Our main focus is then to explore whether, and to which extent, the heterogeneity in climate-change opinions affects retail trading behavior in this scenario. If pro-cliamte-change opinions negatively affect retail trading of climate incident firms, we expect to see that the net demand of retail investors decreases more for firms whose representative investors have higher pro-climate-change opinions. With the inclusion of local climate change opinion measures, we find that, following the disclosure of climate risk incidents, the local beliefs (or concerns) in climate change on average decrease the retail investors' net demand in trading volume of the incident stock by 3.652% (2.582%), equivalent to 21% (15%) of the standard deviation of the net demand measure. Our results are quantitatively and qualitatively very similar when measuring net demand in numbers of retail trade, also robust when varying the retail investor representative base by only including the headquarter or expanding to have more operating counties.

Further analyses draw the economic implication that a firm with negative climate risk disclosure would suffer retail net selling if more than 73.5% (or 71.3%) of its retail investors believe in (or worry about) global warming, a threshold that only 33.1% (or 23.9%) counties in the U.S. mainland met in 2014 and 74.9% (or 50.3%) of them met by 2023. Applying more granular data based on YCOM, we also find that retail investor behavior is influenced by pro-climate opinions across multiple dimensions. These include (1)egoistic concerns–such as the belief that "global warming will harm me personally", (2)altruistic concerns–like the belief that global warming will harm people in developing countries or future generations, and (3) beliefs in renewable energy and support for government and school initiatives to combat global warming.

One concern is that our measure of investor climate-change opinions may also capture the views of other stakeholders (e.g., officers, directors, employees) who reside in firms' major locations. Following a negative climate incident, firms with pro-climate-change stakeholders may take corrective actions to align their operations with prevailing sentiment. However, such measurement error would bias against finding a negative effect on retail trading. Investors anticipating this response would react less negatively, leading to a smaller decline in net demand and a positive effect of the opinion measure—contradicting our empirical findings. Furthermore, we find little evidence that pro-climate-change opinions are informative for the disclosure of future climate incidents at either the firm or county level.

Our main results hold in additional tests controlling the demographics of the retail investor representative base and applying education as an instrumental variable (IV) for climate-change opinions, which together alleviate the concern of omitted variables related to retail investors' risk aversion. To further address this concern, we conduct a wide range of placebo tests by testing other ES incidents disclosed in RepRisk. We find that the effect is topically specific, that is, unique to climate risk incidents, rather than simply a general reaction to any ES-related tail events. If our findings merely reflected retail investors risk aversion in general, we should see a similar change in retail trading on firms following those other risk incidents. In contrast, the results highlight the nuanced role of climate-change opinions: such beliefs and concerns significantly influence retail investors' reactions to risk incidents related to GHG and other related climate-change issues. They have a limited impact on other environmental issues, such as toxic water pollution, and exert minimal influence on social issues, which encompass a broader range of topics less directly linked to global warming.

According to the local bias assumption, our findings should be more pronounced for firms that are prone to be local bias targets. We provide evidence of considerable heterogeneity in our main results by firms' geographic layout, firm size, and the number of operating counties or states. We find that the influence of climate change opinions on retail trading of climate incident firms becomes stronger when the firm is smaller or when its geographical layout is more concentrated and covering smaller number of counties or states. Additonal heterogeneity tests also show that, our main result is strengthened by the severity, novelty of those incidents and the reach of incident news sources, but it is not simply driven by local political leaning of the representative retail investor base.

In the final part of the paper, we use data from Robinhood Markets Inc. (Robinhood) to construct alternative measures of retail investor trading. We investigate whether local climate-change opinions influence this subgroup of retail investors, who are more likely to be younger and newer to investing.[3] Our findings show that both climate change beliefs and concerns reduce the activeness and the number of Robinhood users holding firms associated with climate risk incidents. In contrast, when local climate-change opinions are not considered, the disclosure of climate risk incidents does not significantly affect the number of Robinhood users holding these firms. These results align with our findings from TAQ data. Overall, they suggest that climate risk incidents prompt a reaction from retail investors only when they believe in or are highly concerned about climate change.

It is worth noting that, to assess the robustness of our findings, we rule out firms' other financial news overlapping with the climate risks incident window such as earnings announcement, any variations constant for each firm-incident window such as the industry in which it operates or its recent operational or financial performance. Results are similarly not driven by the seasonality related to weekdays or months in retail trading. Our results are further robust to a wide range of model specifications.

Our findings enrich the nascent investment literature on the relevance of ESG signals to retail investors, which has discovered mixed evidence. For example, retail investors have been shown to act on extreme weather events (Choi et al., 2020; Liu, Zhang, Zhang, and Li, 2023; Yu, 2023); they also trade on financially material ESG news (Li et al., 2024), but such news may not be well suited to drawing inferences about retail investors' nonpecuniary investment decisions (Sloan, 2024). In addition, research finds that Robinhood users do not respond to ESG disclosures (Moss et al., 2024). Our findings highlight the important role played by pro-climate-change opinions, which encompass both pecuniary and nonpecuniary motives, in understanding how retail investors respond to climate risk signals. Additionally, the RepRisk incidents data that we utilize broadly cover ESG incidents with negative risk implications and are free of financial materiality bias.

Our paper also contributes to the growing literature that empirically examines retail investors' motivations for ESG investing. Prior research, based on surveys and experiments with Dutch investors and pension fund participants, has linked participation in sustainable investments to prosocial preferences and altruistic attitudes (Riedl and Smeets, 2017; Brodback, Guenster, and Mezger, 2019; Bauer, Ruof, and Smeets, 2021; Heeb et al.,

[3]See the disclosure by Robinhood and web traffic statistics from SimilarWeb.

2023). Giglio et al. (2024) conducted a one-and-half-year survey of Vanguard clients, highlighting the significance of both pecuniary and non-pecuniary motives. Our study specifically examines retail investors' perceptions of climate change and their influence on managing climate risk in stock investment, where investor participation is not limited to sustainable investments on ESG or SRI funds. Additionally, we adopt an event study framework, leveraging long-term archival data to provide a broader perspective on retail investor behavior.

Recent research utilizing opinion data from YCOM shows that climate change beliefs are reflected in house price variations (Bernstein et al., 2019; Baldauf et al., 2020) and households' reallocation of deposits to pro-climate banks (Dursun-de Neef and Ongena, 2023); climate change concerns also influence the pricing of sea-level rise in both municipal bonds (Goldsmith-Pinkham et al., 2023) and housing and mortgage markets (Keys and Mulder, 2020). Echoing these findings, which underscore the implications of long-term climate change risks, our study integrates both "belief" and "concern" in assessing climate-change opinions and demonstrates their impact on retail investors' reaction to climate risk.

Lastly, our findings are linked to the broad literature on climate finance about the role of climate risk in affecting returns and investments in financial markets. For recent reviews of this growing field, see Giglio, Kelly, and Stroebel (2021), Stroebel and Wurgler (2021), and Hong, Karolyi, and Scheinkman (2020).

2 Empirical Measures and Sample Construction

To assess how the retail investors' response to climate risk is affected by their climate change opinions, we need to construct a dataset composed of three different aspects. The first aspect captures the disclosure of companies' climate risk incidents. The second aspect identifies firm-level retail investors' climate change-related opinions. The third aspect measures firm-level retail investor trading. This section describes the data sources used, the construction of measures in these layers, and the final test sample.

2.1 Firm-Level Climate Risk Incidents

We rely on RepRisk to identify firm-level negative news incidents that are directly linked to climate change issues. Starting from 2007, RepRisk screens daily and globally over 150,000 public sources and stakeholders in

23 languages, covering print and online media, non-governmental organizations, government bodies, regulators, think tanks, newsletters, social media (e.g., Twitter), blogs, etc., to systematically identify any company or project associated with an ESG risk incident. Once an incident is identified, RepRisk analysts conduct additional filtering and analyses to verify ESG issues, remove duplicates, and classify the nature of the incident into detailed ESG categories. Besides the incident records, a risk index (the RepRisk Index RRI) is also constructed for each firm based on a proprietary formula of incident counts and scores. The RRI develops overtime and is recalculated when there is a new risk incident for a firm. It ranges from zero (lowest) to 100 (highest), the higher the value, the higher the risk exposure.

This dataset of negative ESG incidents with daily granularity serves well for our study.[4] Firstly, its event-driven approach reduces the selection bias on covered firms, as incidents are recorded without a pre-defined firm coverage list. Secondly, RepRisk only considers negative news from external sources thus it alleviates the endogeneity concerns that changes in a firm's perceived reputation may be driven by green-washing activities and/or discretionary disclosures.[5] Thirdly, RepRisk identifies a wide range of 28 ESG issues and provides information on a broad picture of firms' ESG risks and violations rather than only covering financially relevant news, as a result, it does not necessarily have a pecuniary focus.

To further zoom in on incidents that are directly linked to climate change, we focus on the following types of incidents according to RepRisk ESG topic tag definitions: greenhouse gas (GHG) emissions and pollution, coal-fired power plants, and drilling (including arctic drilling, deep sea drilling, and offshore drilling). These activities worsen global warming and cause the issue of climate change.[6] It is noteworthy that the tags are not assigned exclusively and the majority of climate incidents in our sample are linked to greenhouse gas (GHG) issues as shown in Panel A of Table 1. Over half of incidents are greenhouse gas (GHG) pollution and emissions. We also plot the number of climate incidents by year during 2014 to 2023 in Figure 1 and decompose the climate incidents by four groups defined above. There is a general upward trend in terms of frequency of such incidents in the later sample period

[4]The data have gained increasing popularity in recent socially responsible investing related studies, see, e.g., Derrien, Krueger, Landier, and Yao (2025); Bansal, Wu, and Yaron (2022); Gantchev, Giannetti, and Li (2022).

[5]Our focus on negative events is consistent with previous ESG-related studies which also emphasize negative qualities such as emissions levels or violations of environmental regulations. Meanwhile, positive events are less likely to be reported in the media and more likely to be self-reported.

[6]The detailed definitions of these ESG topic tags from RepRisk documentations are listed in Appendix Section A.2.

Besides categorizing these incidents by their issues, RepRisk also provide degrees of their severity, reach, and novelty, ranging from 1 to 3 (or up to 2 for novelty) in ascending order of their strength. We show these distributions in Panel B of Table 1. The severity variable describes an incident's impact considering its incident types and consequences. Over 65% climate incidents are less severe, around 32% are severe, and only 2.79% are considered very severe. The reach variable measures how widespread the information source is, according to their readership and circulation. Around 49% of climate incidents are coded as limited reach, while 35% are coded medium reach and 15.7% are considered high reach. Lastly, the novelty measure describes whether it is the first time a company is exposed to this issue. In our climate incident sample, new issues and re-occurring issues are relatively evenly distributed, accounting for 42.73% and 57.27% respectively.

2.2 Local Opinions towards Climate Change

We use the Yale Climate Opinion Map (YCOM) data to capture the local belief and concerns on climate change issues. This dataset is derived from "Climate Change in the American Mind", a biannual national survey conducted since 2008. The survey is led by the Yale Program on Climate Change Communication and the George Mason University Center for Climate Change Communication, in collaboration with a multidisciplinary research team comprising psychologists, political scientists, statisticians, communication specialists, and journalists. The survey consists of four main sections: beliefs, risk perceptions, policy support, and behaviors. Each section includes questions that emphasize different aspects of global warming—the primary driver and most direct evidence of climate change—to gauge public understanding of its causes and consequences.

The YCOM then depicts the percentage of American adults who hold particular beliefs, attitudes, and policy preferences about global warming. The estimates were generated from a statistical model that incorporates actual survey responses, but combines these responses with demographic data such as gender, race, and education from the U.S. Census, they also take into account changes in public opinion over time.[7] As the most comprehensive of their kind in the United States, the YCOM data have gained increasing popularity among researchers, including financial scholars to measure climate change opinions (e.g., Bernstein et al., 2019; Baldauf et al., 2020; Addoum

[7]The details of the model and trends are described in Howe, Mildenberger, Marlon, and Leiserowitz (2015) and Marlon, Wang, Bergquist, Howe, Leiserowitz, Maibach, Mildenberger, and Rosenthal (2022), respectively.

et al., 2023; Goldsmith-Pinkham et al., 2023; Dursun-de Neef and Ongena, 2023).[8]

The county-level survey results in the YCOM started in 2014. We focus on the responses to two key questions: "Do you think global warming is happening?" and "How worried are you about global warming?". Based on the survey design, the first question is to measure "belief", and the second one is to measure "risk perception", thus, we name them "belief" and "concern", respectively, which comprehensively measure public opinions toward climate change. By leveraging YCOM's localized estimates, we capture nuanced geographic variations in climate attitudes across the United States. Appendix Figures IA.1 and IA.2 map the county-level values of these two measures from 2014 to 2023. Although both climate change beliefs and concerns display geographical differences across the country, they also have become more prevalent over the last 10 years.

In accordance with the assumption of local bias in retail investors, we define a firm's representative retail investor base as consisting of investors located in its major operating counties including its headquarter. To do so, the county-level climate change opinion data is combined with the National Establishment Time-Series (NETS) database of Walls and Associates for firms' annual footprints layout and the SEC 8K filing for historical headquarters information.[9] We also consider the substantial regional variation in stock market participation (Hong et al., 2004), which could affect the representativeness of local investors. Following Lin (2020), we measure a county's stock market participation by the ratio of its aggregate dividend income over adjusted gross income (*Div ratio*), using the SOI (Statistics of Income) data from the IRS, which are based on all households that file tax returns with the IRS.

We then construct the retail investors' climate change opinion measure for firm i in year y as:

$$Opinion_{i,y} = \sum_{c \in RIRC_{i,y}} Weight_{c,y}^{Div\ ratio} \times YCOM\ Opinion_{c,y}, \tag{1}$$

where c denotes counties, and $RIRC_{i,y}$ is the set of counties treated as firm i's *Retail-Investor-Representative Counties*. In our main test, we take $RIRC$ as counties where firm i allocates its headquarter or operates with the

[8]The data are applied in the broader studies of economics, environmental studies, or political science and public policy, see, for example, Ballew, Marlon, Goldberg, Maibach, Rosenthal, Aiken, and Leiserowitz (2022), Lee, Goldberg, Rosenthal, Maibach, Kotcher, and Leiserowitz (2024), and Marlon, Wang, Mildenberger, Bergquist, Swain, Hayhoe, Howe, Maibach, and Leiserowitz (2021).

[9]The headers of SEC 8-K filings contain headquarters zip codes, and we then map them to county FIPS codes.

highest share of establishments in year y.[10] For an average firm in our sample, counties in $RIRC_{i,y}$ represent 25% of the firm's footprints, thus we treat $RIRC$ as the representative of a firm's retail investor base. $Weight_{c,y}^{Div\ ratio}$ denotes the weight assigned to each county in $RIRC_{i,y}$ based on their stock market participation measured in $Div\ ratio_{c,y}$. $YCOM\ Opinion_{c,y}$ reflects the public opinion on climate change in each county, measured in either "belief" or "concern". Conceptually, this time-varying location-weighted measure treats these counties as representative of a firm's retail investor base, taking into account both the firms' geographical layout and the level of stock market participation in each county. Alternatively, we also change the set of representative counties $RIRC_{i,y}$, either expand to counties where the firm operates with the top three highest shares of establishments or only contain the firm headquarter. The corresponding alternative measures following Eq. (1) are named $Opinion(Major)$ and $Opinion(HQ)$, respectively.

[Table 2 here]

Table 2 reports the summary statistics of the climate change opinion measures for retail investors in the matched firm-incident sample with RepRisk climate incidents from 2014 to 2023. As shown in Panel A, the average $Belief$ score is 73.10, which means that, for an average climate incident firm, 73.1% of the population in its retail investor base counties believe in climate change. This score averages 71.61 if we consider a firm's broader geographical presence and 74.03 based on its headquarter county. For an average climate incident firm, 63.3% to 65.34% of the population in its retail investor base counties are worried about climate change. These $Concern$ scores are relatively lower than the $Belief$ scores but follow similar patterns. $Belief$ ($Concern$) variables have a standard deviation between 5.18 to 6.14 (6.36 to 7.31), indicating substantial variation in climate change opinions across counties. This divergence provides an ideal empirical setting for testing our research questions. In Panel B, the high correlations within the group of $Belief$ or $Concern$ show that different versions of either opinion measure are significantly correlated. Plus, $Belief$ and $Concern$ are also highly correlated, implying that populations who believe in climate change tend to express concerns about climate change as well.

[Figure 2 here]

[10] Following Kruttli, Roth Tran, and Watugala (2025), we calculate the share of firm i's establishments in a county c in year y as $\frac{Establishment_{i,c,y}}{Total\ establishment_{i,y}}$

A possible concern is that the matched sample in Table 2 might be subject to selection bias, potentially leading to limited variation in climate change opinions. However, the opinion measures of climate incident firms in Table 2 are closely aligned with those of the Compustat firm universe (Appendix Table IA.1) or the RepRisk firm universe (Appendix Table IA.2). As shown in Figure 2 (Appendix Figure IA.3), the distributions of both *Belief* and *Concer* are similar between the sample of climate incident firms and that of the Compustat firm universe (or the RepRisk firm universe), even though the climate incident sample exhibits a slightly higher lower bound and thus a shorter left tail. These comparisons alleviate the concern that the climate incident firms are systematically biased in terms of retail investors' climate change opinions. Additionally, Figure 3 provides snapshots of the YCOM map at the beginning, the midpoint, and the end of our sample period (2014, 2019, and 2023, respectively), with the major locations (footprint and headquarter) of climate incident firms highlighted in red boundaries. It reveals that, over the years, these climate incident firms of our interest have broad geographic distribution across regions from high to low climate change opinions.

[Figure 3 here]

2.3 Retail Investor Trading

Our approach for identifying retail trading relies on the methodology of Boehmer et al. (2021) (BJZZ) to identify retail trades in TAQ as those executed off exchanges and receiving subpenny price improvement. We also follow BJZZ to assign retail trades as buys or sells and apply a buy-sell imbalance measure, which is defined as the difference between retail buy and retail sell scaled by total retail trading, for retail investors' net demand.[11]

Additionally, We complement our main analysis by testing a specific sample of retail investors: those using the Robinhood trading platform.[12] Robinhood users are more likely to be young and new investors with lower balances in accounts. Even though the publicly available data of Robinhood user holding is relatively short (from May 2018 to August 2020), it could provide supplemental evidence of how climate change opinions influence retail investor trading.

[11]Recent papers that follow BJZZ and analyze retail order imbalance include Barber, Lin, and Odean (2023); Farrell, Green, Jame, and Markov (2022); Bradley, Jame, and Williams (2022). A recent work by Barber et al. (2024) documents that the use of quote midpoints following Lee and Ready (1991) to sign trades is more accurate than the use of the subpenny digit. In untabulated robustness tests, we also consider signing trades using the Barber et al. (2024) and find similar results.

[12]The Robinhood users record data is downloaded from https://robintrack.net.

2.4 Other County-level Data

To capture the effect of county demographics and economic development on climate change opinions of local investors and their trading activities, we include a list of county-level variables and estimate the impact of climate change opinions conditionally on the list. We use the annual Census Bureau's Population and Housing Unit Estimates to proxy for the ethnicity and age of the local population. Education attainment is measured using the Census Bureau's American Community Survey (ACS) five-year estimates. Besides these demographics, we also include variables on local economics, such as per capita personal income from the Bureau of Economic Analysis (BEA)'s Personal Income by Count annual data, and the Federal Housing Finance Agency (FHFA) annual county-level house price indices and their changes.

Following a similar approach in Eq.(1) and taking $RIRC_{i,y}$ as the set of counties where firm i allocates its headquarter or operates with the highest share of establishments in year y, we aggregate these county-level variables to the firm level. Conceptually, these firm-level variables describe the characteristics of $RIRC_{i,y}$ outlined above, including $Income_{i,y}$, $HouseValue_{i,y}$, and $HouseReturn_{i,y}$. For other variables, we select a year, 2010, which is earlier than our sample period, and construct $Education$, Age, and $White$ as static values throughout the sample, similar to the approach in Lin (2020).

2.5 Sample Description

Starting with RepRisk matched with local climate change opinions as described in section 2.2, we include climate-related incidents of U.S. public firms from 2014 to 2023, exclude financial firms (SIC codes between 6000 and 6999), and link the rest to COMPUSTAT and TAQ. Our final sample includes 1,487 unique climate incidents by 495 unique firms. Taking together, there are 5,024 firm-incident observations. One average firm has roughly 10 climate incidents throughout the sample period, averaging three or four incidents per year.

Following Li et al. (2024), we use a $[-20, +20]$ trading-day window around each climate incident. Combined with retail trading data, we have 205,460 Firm-Incident-Day observations.

[Table 3 here]

As shown in Table 3, on average, retail trading imbalance measured by volume is -1.63%, and the similar

measure by trade is 3.99%, showing that these firms have active retail trading in the market. To consider the earnings announcement market impact, we identify if an earnings announcement happens within the incident's trading window. For roughly one-third of firm-level climate incidents, a [−20, +20] trading-day window overlaps with earnings announcement dates.

Regarding the county-level variables, we report their summary statistics in the Firm-Incident-Day Sample sample. One average county in the sample has two million residents. Over 33% of the population aged above 25 years old own a bachelor's degree or above, 52% of its population identifies as White, and the median age is 35 years old. It has on average 70,080 dollars in annual income per capita and a 7% house value increase per year.

We also examine the other ES incidents in RepRisk and construct a similar firm-incident-day sample. For non-climate environmental incidents, there are 8,363 firm-incident observations by 650 unique firms. Similarly, we construct a [−20, +20] trading-day window for these incidents, and end up with a sample of 341,691 firm-incident-day observations as shown in Appendix Table IA.5 Panel A. Following the same approach, we construct a non-climate social incident sample, which includes 15,954 firm-incident pairs by 1,052 unique firms. Appendix Table IA.5 Panel B shows the summary statistics of this sample, including 652,026 firm-incident-day observations.

3 Climate Change Opinions and Retail Trading

This section presents evidence of a link between local climate change opinions and retail investor response to climate risk incidents.

3.1 Empirical Setup

Our central research question is the extent to which climate change opinions affect retail investors' response to climate risk incidents. As discussed above, our regression sample consists of firm-incident-day observations in the 20 trading-day before and after each negative climate incident for the corresponding firm-incident pair. We estimate the following regression model:

$$Retail\ Imbalance_{i,e,t} = \beta_1 Incident_{i,e,t} \times Opinion_{i,y} + \beta_2 Incident_{i,e,t} + \beta_3 EA_{i,t} + \alpha_{i,e} + \gamma Control_{i,t} + \epsilon_{i,e,t}. \quad (2)$$

The outcome variable of interest is the buy-sell imbalance in volume or number of retail trades on day t for the pair of firm i and incident e. $Incident_{i,e,t}$ is an indicator equal to one if the date t is within one week (five trading days) of the firm-incident of climate risk incidents. Following the definition in Eq. (1), $Opinion_{i,y}$ is the climate change opinion of retail investors of firm i in the event year y, either in $Belief$ or in $Concern$. Alternatively, we also apply $Opinion(Major)_{i,y}$, considering more major locations, or $Opinion(HQ)_{i,y}$, only considering the headquarter. We expect β_1 to be negative if retail investors with pro-climate-change opinions negatively respond to incidents with climate risk.

We control for a number of other factors that may influence retail trading. For example, observations in our sample could be affected by other firm-level events such as earnings announcements, if they are within the corresponding event window. Therefore, we use the dummy variable $EA_{i,t}$ to flag if day t is within the [-20, 20] trading-day window of firm i' earnings announcement.[13] Plus, we include the firm-incident fixed effect ($\alpha_{i,e}$) to absorb any variations constant for each firm-incident window. Importantly, it controls for a number of alternative explanations which are the time-invariant within the 40-trading-day event window, such as influence from political partisanship in a firm's headquarter location, the industry in which it operates, or its recent operational or financial performance. We also control other firm-day characteristics in $Control_{i,t}$ including the seasonality of day t related to weekdays and months, and whether day t overlaps with another event window of firm i. We cluster the standard errors ϵ in two ways: by firm and by incident.

One concern is that our measure of investor climate-change opinions may also capture the views of other stakeholders (e.g., officers, directors, employees) who reside in firms' major locations. Following a negative climate incident, firms with pro-climate-change stakeholders may take corrective actions to align their operations with prevailing sentiment. However, such measurement error would bias against finding a negative effect on retail trading. Investors anticipating this response would react less negatively, leading to a smaller decline in net demand and a positive effect of the opinion measure—contradicting our empirical findings. Furthermore, we find little evidence that pro-climate-change opinions are informative for the disclosure of future climate incidents at either the firm or county level in Appendix Table IA.4.

[13]The results are robust when we exclude climate risk incidents that occur on the same day of a firm's earnings announcement in Appendix Table IA.3.

3.2 Main Results

Table 4 represents the key results, with the net demand of retail investors measured by trading volume in Panel A and by the count of trades in Panel B.

[Table 4 here]

In column (1) of Panel A, the coefficient for *Incident* does not show statistical significance, aligning with previous literature that finds no evidence suggesting ESG disclosures influence an average retail investor(Moss et al., 2024). This result implies that, without accounting for heterogeneity among investors, such as differences in opinions, retail investors on average do not react to climate risk incidents.

Turning to the variable of interest, columns (2) to (7) present the baseline specifications in Eq. (2), with *Opinion*, or its alternatives of $Opinion(Major)$ and $Opinion(HQ)$, measured by *Belief* in columns (2) to (4) and by *Concern* in columns (5) to (7). The key coefficient β_1 is negative and statistically significant throughout the columns, which indicates that pro-climate-change opinions negatively affect retail investors' net buying of stock shares right after the firm suffers negative incidents related to climate change risk. For example, in column (2) (column (5)), the coefficient estimate of $Incident \times Opinion$ is -0.049 (-0.042). Considering the average values of *Belief* (*Concern*) that 73.10% (64.55%) of retail investors per firm believe in (worry about) climate change, we can draw the economic implication that the climate change belief (concern) on average decreases retail investors' net demand by 3.582% (2.711%) measured by trading volume, and this drop is equivalent to 21% (16%) of the standard deviation of this net demand measure. The results are similar when we apply the alternative measures of $Opinion(Major)$ or $Opinion(HQ)$ in the remaining columns.

A further comparison between the estimates of β_1 and β_2 also helps us better understand the economic significance. For example, column (2) of Panel A, with β_1 of -0.049 and β_2 of 3.625, implies that, to generate a negative retail investor response to climate risk incidents, the threshold of the climate change belief score is 3.625/0.049=74; a similar comparison for coefficients in column (5) yields the threshold of climate change concern score of 66.6. Putting together, a firm with negative climate risk disclosure would suffer retail net selling if more than 74% (or 66.6%) of its retail investors believe in (or worry about) global warming. Projecting these numbers to the YCOM map of beliefs and concerns about global warming, we find that among all U.S. mainland counties with

Compustat firm footprints, only 33.1% (or 23.9%) met this threshold in 2014; by 2023, this percentage increases to 74.9% (or 50.3%), highlighting the investment implications of the substantial increase in pro-climate-change opinions over the past decade.

It is worth noting that the β_1 coefficient remains negative and statistically significant when we control for the earnings announcement window across columns. Specifically, if a firm-day falls within the [-20, 20] trading-day window around the firm's earnings announcement, the average increase of retail net buying ranges from 0.75% to 0.80%, as measured by volume imbalance. In comparison, the economic effect of climate change opinions discussed above is considerably large.

In Panel B of Table 4, we replicate these analyses above using $Retail\ Imbalance(Trade)$ as our dependent variable of interest, which is a nosier measure of retail net buying that considers only the count of trades. Comparing the coefficients across the two panels confirms the robustness of our negative β_1 estimates on $Incident \times Opinion$.

3.3 Detailed Survey Questions in the YCOM

Following Eq. (1), we also construct detailed firm-level retail investor opinion measures based on detailed questions in the survey. We repeat the tests from Table 4 using those detailed climate change opinion measures and present the significant results in Table 5.

[Table 5 here]

For nine questions, we find a significant negative effect of climate change beliefs or risk perceptions on retail investor trading after climate change risk incidents. The details of these questions are:

(1)$Personal$: global warming will harm me personally.

(2)$HarmUS$: global warming will harm people in the United States.

(3)$Consensus$: agree that most scientists think global warming is happening.

(4)$FutureGen$: global warming will harm future generations of people.

(5)$HarmDev$: global warming will harm people in developing countries.

(6)$Human$: global warming is caused mostly by human activities.

(7)*Governor*: Governor should be doing more or less to address global warming.

(8)*SupportRenew*: support that requiring utilities to produce 20% electricity from renewable sources.

(9)*TeachGW*: schools should teach about global warming.

[Figure 4 here]

In Figure 4, we also plot the economic significance value of the interaction term of each question with *Incident* in tests above. Among the nine questions, some are closer to egoism (e.g.,*Personal*), some are closer to altruism or pro-social preference (e.g.,*FutureGen*, *HarmDev*), some are the mix of both. Together, the tests indicate that the effect of pro-climate opinions on retail investors are related to mixed motivations.

3.4 Climate Incidents v.s. Other ES Incidents

A potential confounding issue in our setup is the presence of omitted variables that may influence these opinion measures. On the one hand, these variables could be associated with retail investors' risk aversion, which might drive retail trading following risk incidents. If this is the case, any change in retail investor trading could simply reflect a general reaction to tail risk events rather than a specific response to climate risk incidents. On the other hand, the climate risk incidents we focus on also carry significant environmental and social consequences (see the Internet Appendix Section A.2), thus our opinion measures might merely reflect omitted variables related to investors' responses to any rare environmental or social catastrophe, rather than being specific to climate change. To address these concerns, we contrast our results on climate change risk incidents with the rest of Reprisk ES incidents that are not directly linked to climate change. As illustrated in Appendix Figure IA.5, industry distributions differ between firms with climate incidents and those with other ES incident: approximately 41.5% of firms with climate incidents operate in the consumer durables sector, whereas firms with other ES incidents are more broadly distributed. However, the distribution of *Retail Imbalance* and climate change opinions are similar, as shown in Appendix Tables IA.5 and IA.6.

We extend the firm-incident-Date sample to include all RepRisk incidents and construct three incident indicators: *Incident* follows the same definition in section 3.1 to mark climate incidents, while $Incident^{other\ E}$ or $Incident^{other\ S}$ is an indicator equal to one if the date t is within one week (five trading days) of the firm-incident

of environmental (E) or social risk (S) incidents which exclude these climate risk incidents. If the negative effect on retail trading captured by our specifications truly reflects the impact of climate change opinions, the occurrence of risk incidents that are less (or even not) directly linked to climate change should not trigger comparable effects of these opinions on retail trading. Applying the three variables in a regression model similar to Eq. (2), we test if climate change opinions have a comparable effect on retail investors' reactions when facing negative ES events that are not directly linked to climate change. The results are reported in Table 6.

[Table 6 here]

In columns (1), (4), and (7), the coefficient estimates on the three incident indicator variables are statistically insignificant, which means that an average retail investor neither responds to climate risk incidents nor other ES incidents. However, after incorporating climate change opinion measures in columns (2) and (3), the coefficients of $Incident \times Opinion$ are negative and significant, close to the main findings in Table 4. Similarly, the coefficients of $Incident^{Other\ E} \times Opinion$ are also negative and significant, albeit with reduced magnitude and lower statistical significance. This suggests that, while climate change opinions influence retail investor reactions to environmental incidents not directly tied to climate change, the effect is weaker compared to incidents involving GHG emissions and closely related risks. In contrast, the coefficients of $Incident^{Other\ S} \times Opinion$ are insignificant and display inconsistent signs. These results highlight the nuanced role of climate change opinions: such beliefs and concerns significantly influence retail investors' reactions to risk incidents related to GHG and other related climate change issues, they have a limited impact on other environmental issues, such as toxic water pollution, and exert minimal influence on social issues, which encompass a broader range of topics less directly linked to global warming.

In columns (4) to (9), we also examine those other ES incidents alone in a parallel test to Eq. (2). The results are consistent with a perception that those events would not lead to significant retail investor responses even when local climate change beliefs are high.

3.5 Determinants of Climate Change Opinions and IV estimation

The original YCOM data is closely linked to local demographics, thus it is not surprising that we also find that the firm-level climate change opinions are related to demographics in firms' major locations. As shown in Appendix

Table IA.8, these opinions increase with county populations or decrease in counties with more white populations, climate change concerns are also significantly higher in counties with higher housing values. However, neither opinion measure seems to be affected by housing returns or income per capita. In addition, both belief and concern have a statistically significant correlation with education.

We next consider the possibility that these demographics of retail investors may affect our findings, even though in our main test of Eq. (2), the firm-incident fixed effect $\alpha_{i,e}$ already absorbs these characteristics alone. Given that we test the effect of climate change opinions by interacting with *Incident*, it is still possible that omitted variables could disturb our test through similar interaction terms. We address this issue by including those interaction terms in our main test. Although we do not observe the characteristics of each retail investor, as explained in section 2.4, the related firm-level variables based on county-level demographics contain this information for a firm's representative retail investors base. The test results are reported in Table 7.

[Table 7 here]

In column (1), without climate change opinions, retail trading after climate incidents is not affected by race, income, housing value, and home equity. In contrast, columns (2) to (3) show that the influence of climate change belief or concern in our main findings holds after including all interaction terms with these characteristics above.

We then follow Lin (2020) to use education as an IV for climate change opinions. Education is related to both *YCOM Opinion* and stock market participation (*Div ratio*), the two factors to construct *Opinion* in Eq. (1), and there is no prior direction in which education would affect the net buying of retail investors. Thus, it is very likely that education would be correlated with retail trading after climate incidents only through its impact on climate change opinions. In columns (4) and (5), taking education as a valid instrument, when interacting with *Incident*, negatively affects retail trading, even after including other retail investor demographics measures. These results would further alleviate the concern that our main findings are driven by some omitted variables related to other characteristics of retail investors.

Taken together, the results from Table 4 to 7 are consistent with our main hypothesis that retail investors negatively react to climate change risk incidents, only if they believe in or worry about climate change.

4 Heterogeneity in Climate Change Opinions' Influence

Next, we study the potential role of heterogeneity in how climate change opinions influence retail investors' trading behavior. This analysis explores variation across different firms and incident types. We also provide a wide range of additional robustness tests to ensure that our main findings are not dominated by factors such as news visibility, political leaning, or industry clustering.

4.1 Local Bias

As explained in Section 2.2, We establish the linkage between local climate change opinions and retail investors based on the existence of local bias in retail investing activities. We assume that retail investors located in a firm's primary operating locations, including the headquarter, are representative of its average retail investor. Based on this assumption, our findings are expected to be more pronounced for firms that are more likely to benefit from geographically proximate investments, for example, small firms or regional firms.

To assess the extent to which firms are influenced by local bias, we consider four measures. The first is firm size, measured by the natural logarithm of the market value (MV), as Coval and Moskowitz (1999) find that investors exhibit a strong preference for local firms, particularly small ones. The remaining three variables capture the degree of "localness": the total number of counties or states in which a firm operates; and the Herfindahl-Hirschman Index (HHI) based on a firm's footprint shares in each state to measure the concentration of its geographic presence. Firms with more geographically concentrated footprints, covering fewer counties or states, are considered more local and less nationally recognized, making them more reliant on local investors.

[Table 8 here]

In Table 8, we interact the explanatory variables of interest with these "localness" characteristics variables, which themselves are absorbed by the firm-incident fixed effect. Across Columns (1) to (6), our main coefficient on $Incident \times Opinion$ (either $Belief$ or $Concern$) remains statistically and economically very similar to our main specification. In columns (1) and (2), we find that the estimated coefficient on the triple interaction $Incident \times Opinion \times Ln(MV)$ is positive and statistically significant ($Opinion$ in either $Belief$ or $Concern$), which means the effect of climate change opinion on incident firms is getting weaker with firms growing bigger.

Similarly, columns (3) to (6) show that the effect also weakens as the number of operating counties or states increases.

In column (7), we find that the estimated coefficient on the triple interaction $Incident \times Belief \times HHI^{map}$ is negative and statistically significant, indicating that the previously documented main effect is concentrated among firms with higher levels of geographic concentration. This also suggests that our measure of retail investors' climate change opinions is more applicable to local firms whose operations are clustered within a specific region. Similarly, Column (8), which uses $Concen$, yields comparable results, though the statistical significance is somewhat weaker.

4.2 Incident Properties

If pro-climate-change retail investors react to climate-related risky incidents, their reactions should be strongest for incidents with the most severe consequences. The severity of such incidents could therefore be a possible factor triggering investor responses. To test this conjecture, we categorize climate incidents based on three measures that evaluate their impact.

The first measure is based on the severity scores assigned by RepRisk to each incident, reflecting the magnitude of its perceived impact. We use the $I(Severity)$ dummy to flag incidents classified as "very severe" by RepRisk. The other two measures are derived from changes in a firm's RepRisk Index (RRI), which reflects the firm's ESG riskiness and is recalculated when new incidents occur. Following Houston, Lin, Shan, and Shen (2022), we identify severe incidents by checking whether they lead to an increase in the RRI. $I(Pos.\Delta RRI)$ is a label indicating such incidents and $Pos.\Delta RRI$ represents the corresponding increase in the RRI value.

[Table 9 here]

In Table 9, we estimate the influence of incident severity using a triple interaction between $Incident \times Opinion$ and one of the three severity measures discussed above. The coefficient estimates on the triple interaction terms are negative and economically large across columns, suggesting the negative effect of pro-climate-change opinions on retail trading after climate incidents becomes stronger when the incidents have a harsher impact and expose firms to substantial ESG risks.

It is worth noting that RepRisk also categorizes incidents based on two additional features: novelty, which

captures the newness of an incident—defined as whether it is the first time a firm is exposed to a specific ESG issue in a particular location; and reach, which reflects the readership and prominence of the news sources, ranging from local to national and international outlets. We do not have a clear prior regarding how these features influence our main results. For novelty, investors might respond more strongly either to first-time events or to recurring incidents with increasingly severe consequences. For reach, since retail investors may benefit from a local information advantage (Chi and Shanthikumar, 2017), the scope of news circulation may have a limited effect on their behavior. As reported in Appendix Tables IA.9 and IA.10, we find that the impact of these two incident characteristics is conditional on incident severity: the baseline effect is strongest when incidents are both severe and novel, or both severe and high-reach.

4.3 Local Political Leanings

As a final heterogeneity test, we study the role of political ideology, which is related to investors' prosocial nature, and thus may affect climate change opinions (Anderson and Robinson, 2024).

Our proxies for political leanings are based on county-level outcomes in the latest presidential election when a climate incident occurs. Using data from MIT Election Data and Science Lab. We apply three measures for the political leaning of a firm's representative investor base: $Red_{i,e}$ is a continuous variable defined as the percentage of red counties among firm i's $RIRC$, $I(Red)_{i,e}$ or $I(Blue)_{i,e}$ is an indicator variable for whether a firm i is headquartered in a red or blue county during indecent e, Conceptually, these measures categorize the extent to which a firm is exposed to Democratic or Republican retail investors. We then control the influence of political leanings by interacting $Incident$ with these measures.

[Table 10 here]

As shown in Table 10, across all columns, we find that our main coefficient on $Incident \times Opinion$ remains negative and statistically significant. We also find statistically insignificant interactions of $Incident \times Blue$ (or $Incident \times I(Blue)$). We also separate the firm-incident-day sample to two parts depending on if a firm has red or blue counties in $RIRC$. As shown in Table IA.12, across both subsamples, we find that our main coefficient on $Incident \times Opinion$ remains negative and statistically significant. This indicates that our results continue to hold

when only focusing on firms that are more exposed to Republican or Democratic retail investors. Taken together, these findings suggest that the influence of climate change opinions cannot be simply explained by investors' political leanings. Instead, heterogeneity in climate change opinions within both parties appears to affect retail investor trading behavior.

4.4 Other Robustness Tests

Since more than 40% of climate incidents in our sample are in firms of "consumer durables", which are mainly oil companies associated with activities involving greenhouse gas emissions and pollution, and more directly, drilling (see the Internet Appendix Figure IA.5), it raises questions that retail investors may only react to incidents in certain industries. Besides, the oil industry has long been the center of climate change discussions, and it results in a more negative impression among the public regarding different environmental issues. To alleviate this concern, we show robustness tests on the sample excluding oil-related firms.

We exclude oil-related firms, defined as a SIC code of 1311, 1381, 1382, 2911, and 5171, and test our baseline design. As shown in Table IA.11, the interaction terms of climate incidents and climate change belief measures stay significantly negative. Comparing the coefficients with those in Table 4, this sample without oil-related firms shows a stronger negative effect. Therefore, our results are not driven by the controversial oil industry.

5 Alternative Measures for Retail Trading Using Robinhood

In this section, we use Robinhood user holding records from Robintrack as an alternative retailing trading measure to test our main hypotheses. Different from the retail trading measures based on TAQ data, Robinhood provides an opportunity to look at retail-only investors without the need to distinguish from non-retail trading orders. However, this data has a shorter time span, from May 2018 to August 2020, and does not provide trade-level information. Keeping these limitations in mind, we leverage this dataset to provide more evidence from retail investors on Robinhood.

By merging the Robinhood data with RepRisk and our climate change opinion measures, we construct a

firm-day panel sample that includes 1,832 unique firms. Then we run the following regression:

$$RH_{i,t} = \beta_1 Incident_{i,t} \times Opinion_{i,y} + \beta_2 Incident_{i,t} + \Gamma\ Other_{i,t} + \alpha_i + \phi_t + \epsilon_{i,t}. \tag{3}$$

Following Moss et al. (2024), $RH_{i,t}$ measures the activities of Robinhood users of firm i on day t, either in the change of the number of users from day $t-1$ to $t+1$ or the hourly volatility of the number of users from day $t-1$ to $t+1$.[14] The first one is a proxy of the growth of the retail investor base, and the second one is a proxy of the activeness of retail investor activities. Both measures are scaled by the natural logarithm of a firm's total assets. $Incident_{i,t}$ flags the disclosure date of climate incidents for firm i. We also control other firm events in $Other_{i,t}$, including the earnings announcement date and the disclosure date of other E or S incidents. We also include two sets of fixed effects, firm and date, to fully absorb time-invariant cross-firm heterogeneity and time trends.

[Table 11 here]

As presented in columns (1) and (4) of Table 11, having climate incidents does not affect user growth or user activeness on the Rohinhood platform. Columns (2) and (3)((5) and (6)) show that pro-climate-change opinions negatively affect user growth (activeness) when a climate incident happens. Since the Robinhood data do not provide detailed trading information of its users, this result does not directly speak to strict net selling or net buying. Nevertheless, the findings are consistent with our previous results based on TAQ data. Echoing our main findings, the negative coefficient on $Incident \times Belief$ and $Incident \times Concern$ when focusing on Robinhood users, which implies a deterioration in retail investor activities, provides additional evidence that climate change opinions affect retail trading decisions in dealing with climate change risk.

6 Conclusion

Sustainable investing is motivated in part by beliefs and concerns about climate change. Understanding the drivers of this investment demand is thus crucial to assessing the ability of finance to facilitate a range of sustainability objectives. In this paper, we explore these drivers by combining ten years of county-level survey records with the

[14] To decide a daily user holding count on a firm, we use the hourly observation whose timestamp is closest to 4 PM.

archival data of retail trading. We provide novel evidence that climate risk incidents affect retail investors only when they believe in or are highly concerned about climate change. Our evidence is consistent with theoretical asset pricing work that highlights pro-climate preference being important in investors' decision-making (Pástor et al., 2021).

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Figures

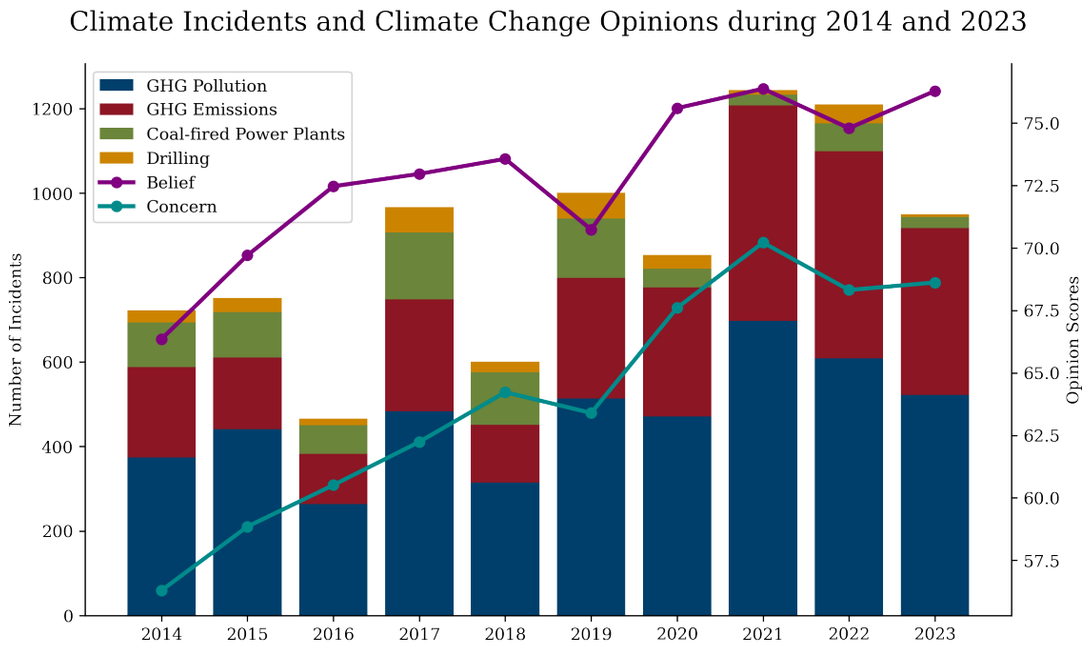
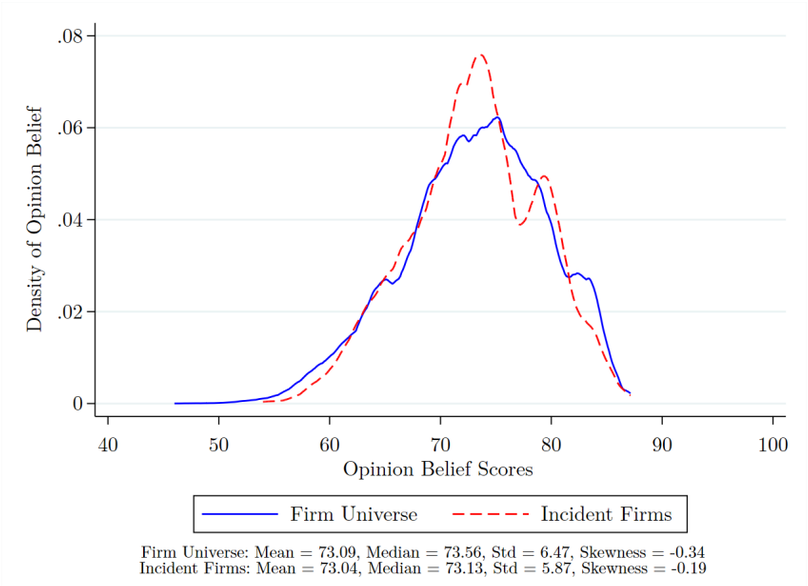
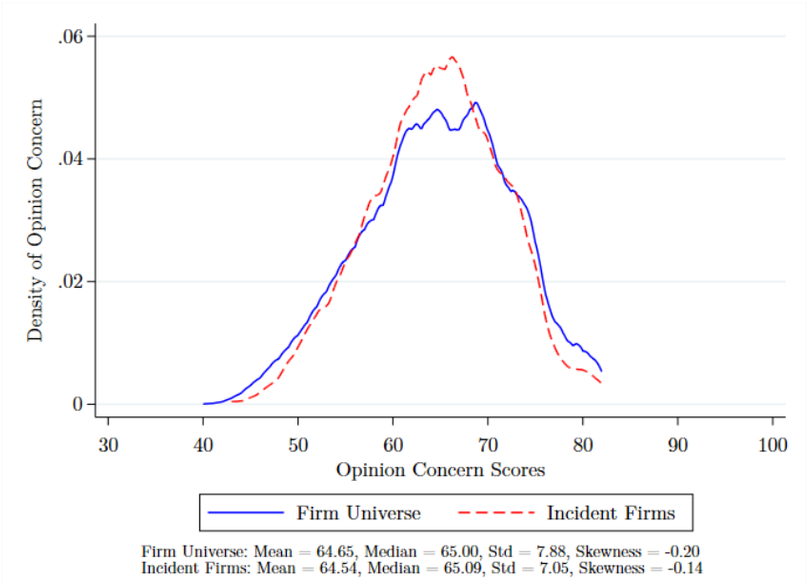


Figure 1: Climate Incidents and Climate Change Opinions during 2014 and 2023
This bar chart shows the average number of the four types of climate incidents as defined in the Appendix A.2. The line chart plots the average climate change opinions (either *Belif* or *Concern*) in the firm-climate incident sample.

Figure 2: Score Distribution
This figure plots the distribution of the climate change opinions, *Belief* in Panel A and *Concern* in Panel B, in our main sample and the sample of the firm universe during 2014 and 2023. The main sample includes firm-level climate incidents, while the firm universe includes firm-year pairs of all firms that have historical headquarter information in SEC 8-k filing.

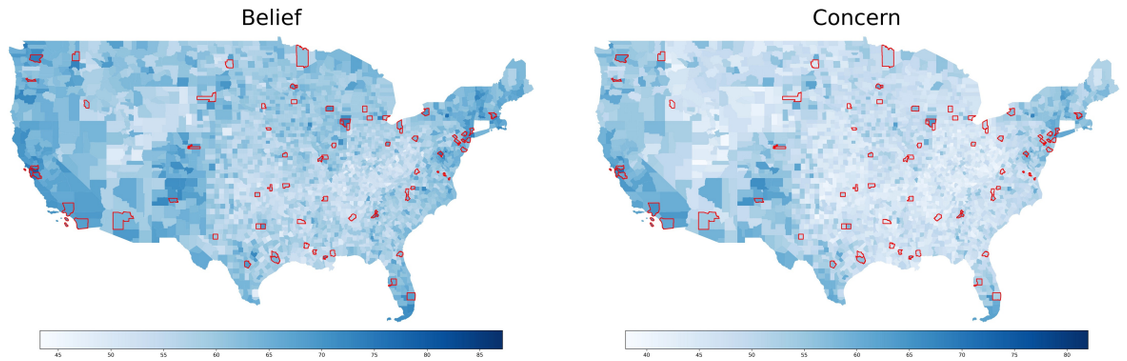


(a) Opinion Belief

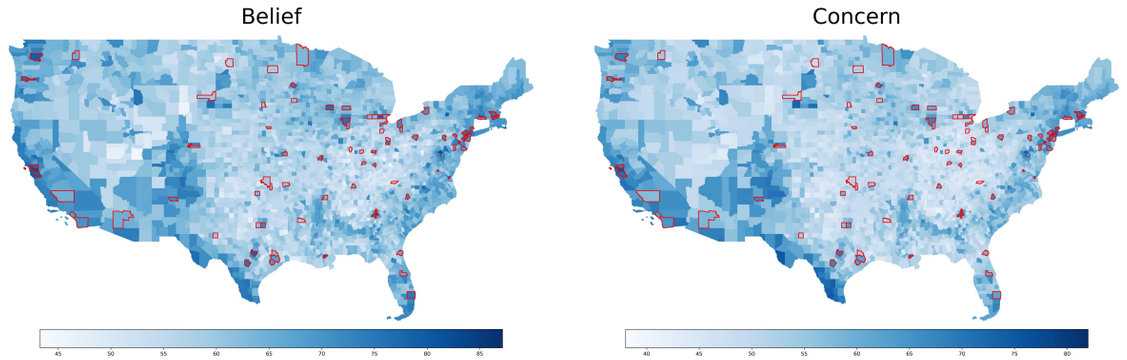


(b) Opinion Concern

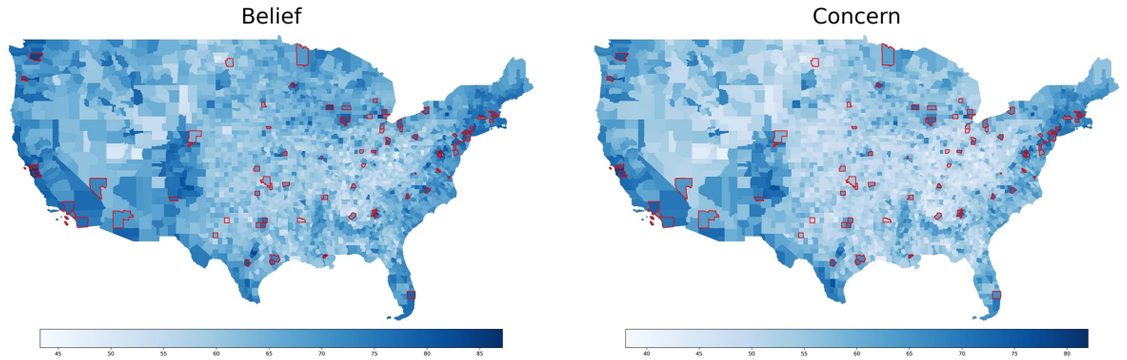
Figure 3: Yale Climate Change Belief Survey Scores
This figure maps the county-level YCOM opinion scores, *Belief* and *Concern*, in 2014, 2019, and 2023. Counties where firms with climate incidents headquarter or operate are highlighted in red.



(a) Climate Change Opinion and Incident Locations in 2014



(b) Climate Change Opinion and Incident Locations in 2019



(c) Climate Change Opinion and Incident Locations in 2023

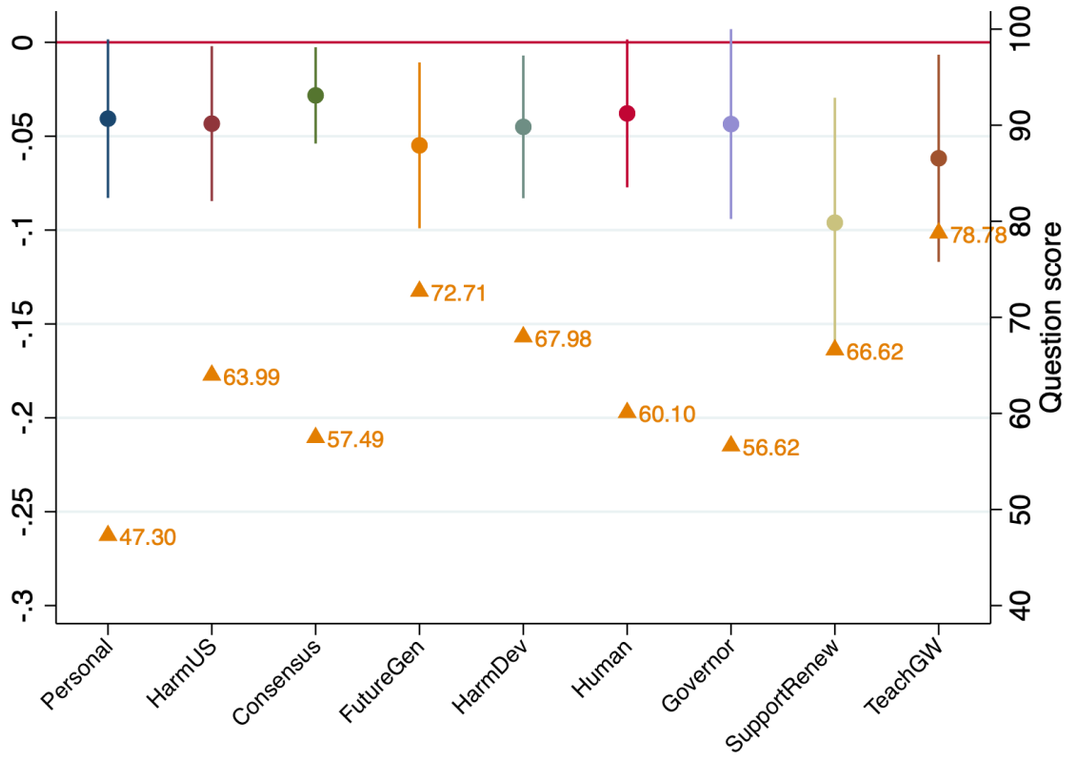


Figure 4: Results on Alternative Climate Change Opinion Measures
This chart shows the point estimates with the 95% confidence intervals of alternative climate change opinion measures in Table 5. The question details are shown in Table A.1. The numbers with triangles represent the question scores that neutralize the retail net demand. A higher score is correlated with a more negative retail demand.

Tables

Table 1: Distribution of Climate Risk Incidents
This table reports the distribution of climate incidents in the main sample from 2014 to 2023. Panel A shows the distribution across four incident categories and Panel B lists the severity, reach and novelty of incidents defined by RepRisk.

Panel A: Distribution of Climate Incident					
GHG Pollution	GHG Emissions	Coal-fired Power Plants	Drilling	Count	Percent
1	0	0	0	1,443	28.72
0	0	1	0	272	5.41
0	0	0	1	63	1.25
1	1	0	0	2,515	50.06
1	0	1	0	223	4.44
1	0	0	1	57	1.13
1	1	0	1	80	1.59
1	1	1	0	247	4.92
1	0	1	1	77	1.53
1	1	1	1	47	0.94

Panel B: Distribution of Characteristics			
	Severity (%)	Reach (%)	Novelty (%)
1	65.27	49.20	57.27
2	31.95	35.07	42.73
3	2.79	15.72	–

Table 2: Firm-level Climate Change Opinion Measures
This table reports the summary statistics of climate change belief measures for firm-climate incident pairs from 2014 to 2023. Panel A includes two sets of variables for *Belief* and *Concern*, following the definition in Eq. (1). Panel B provides the correlation matrix among these variables. All variables are defined in Table A.1.

Panel A: Climate Change Opinion Scores

	N	mean	sd	min	p25	p50	p75	max
Opinion Belief	4,686	73.10	5.92	54.00	69.39	73.26	77.40	87.15
Opinion Belief(Major)	4,686	71.61	5.18	56.49	68.27	72.07	75.44	87.15
Opinion Belief(HQ)	4,686	73.83	6.09	54.00	70.19	74.76	78.52	87.15
Opinion Concern	4,686	64.55	7.09	43.00	59.93	65.02	69.46	81.99
Opinion Concern(Major)	4,686	63.30	6.36	44.36	59.01	63.53	67.42	81.99
Opinion Concern(HQ)	4,686	65.11	7.28	43.00	60.34	65.19	70.44	81.99

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)
Opinion Belief	1					
Opinion Belief(Major)	0.755***	1				
Opinion Belief(HQ)	0.943***	0.724***	1			
Opinion Concern	0.936***	0.725***	0.888***	1		
Opinion Concern(Major)	0.737***	0.940***	0.710***	0.799***	1	
Opinion Concern(HQ)	0.888***	0.695***	0.935***	0.955***	0.769***	1

Table 3: Summary statistics of the Firm-Incident-Day Sample for Climate Risk Incidents
This table reports the summary statistics of our main sample at the firm-incident-day level from 2014 to 2023. All variables are defined in Table A.1.

	N	mean	sd	min	p25	p50	p75	max
Retail Imbalance(Volume)	191,643	-1.68	17.30	-100.00	-9.98	-1.07	6.92	100.00
Retail Imbalance(Trade)	191,643	3.92	15.99	-100.00	-5.00	4.01	13.06	100.00
Opinion Belief	191,643	73.10	5.92	54.00	69.39	73.26	77.40	87.15
Opinion Belief(HQ)	191,643	73.83	6.09	54.00	70.19	74.75	78.52	87.15
Opinion Belief(Major)	191,643	71.61	5.18	56.49	68.27	72.07	75.44	87.15
Opinion Concern	191,643	64.55	7.09	43.00	59.93	65.01	69.46	81.99
Opinion Concern(HQ)	191,643	65.11	7.28	43.00	60.34	65.19	70.44	81.99
Opinion Concern(Major)	191,643	63.30	6.36	44.36	59.01	63.52	67.42	81.99
EA	191,643	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Education	191,643	33.82	9.26	12.70	27.70	30.56	39.10	70.10
Population	191,643	2.05	1.63	0.00	0.79	1.48	3.51	10.09
Income	191,643	70.08	25.59	0.00	53.83	63.02	75.89	193.62
White	191,643	0.52	0.17	0.16	0.34	0.49	0.64	0.96
Age	191,643	35.33	3.13	27.50	32.50	35.28	37.50	52.50
HouseValue	191,643	200.82	59.70	0.00	157.94	194.98	236.60	451.56
HouseReturn	191,643	0.07	0.05	-0.31	0.04	0.06	0.09	0.26
Ln(MV)	191,643	17.51	1.75	8.73	16.38	17.62	19.07	21.77
HHI^{map}	191,643	0.25	0.21	0.03	0.09	0.19	0.31	1.00
Num_county	191,643	4.50	1.44	0.00	3.64	4.80	5.49	7.88
Num_state	191,643	3.00	0.96	0.00	2.56	3.37	3.76	3.97
I(Severity)	191,643	0.03	0.16	0.00	0.00	0.00	0.00	1.00
I(Pos. Δ RRI)	191,643	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Pos. Δ RRI	191,643	3.02	4.93	0.00	0.00	1.00	4.00	40.00

Table 4: Local Climate Change Beliefs and Retail Investor Trading
This table presents results from regressions of retail order imbalance (in percentage) on the interaction of local climate change beliefs with the occurrence of a climate risk incident. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Panel A uses retail trade volume to measure retail trading activities and Panel B uses the number of retail trades. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Retail Imbalance (Volume)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Belief			Concern		
Incident	0.057	3.625**	2.752*	2.999**	2.799**	2.555*	2.202*
	(0.105)	(1.545)	(1.663)	(1.505)	(1.281)	(1.303)	(1.224)
Incident × *Opinion*		-0.049**			-0.042**		
		(0.021)			(0.019)		
Incident × *Opinion*(*Major*)			-0.038*			-0.039**	
			(0.023)			(0.020)	
Incident × *Opinion*(*HQ*)				-0.040**			-0.033*
				(0.020)			(0.018)
EA	0.803***	0.802***	0.802***	0.801***	0.801***	0.802***	0.801***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	191643	191643	191643	191643	191643	191643
R^2	0.111	0.111	0.111	0.111	0.111	0.111	0.111
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days						

Panel B: Retail Imbalance (Trade)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Belief			Concern		
Incident	0.202*	3.009**	2.980*	2.721*	2.530**	2.448**	2.197*
	(0.105)	(1.436)	(1.638)	(1.531)	(1.131)	(1.204)	(1.171)
Incident × *Opinion*		-0.038**			-0.036**		
		(0.019)			(0.017)		
Incident × *Opinion*(*Major*)			-0.039*			-0.035*	
			(0.022)			(0.018)	
Incident × *Opinion*(*HQ*)				-0.034*			-0.031*
				(0.020)			(0.017)
EA	0.118	0.116	0.117	0.116	0.116	0.116	0.116
	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)	(0.145)
N	191643	191643	191643	191643	191643	191643	191643
R^2	0.340	0.340	0.340	0.340	0.340	0.340	0.340
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days						

Table 5: Alternative Climate Change Opinion Measures

This table presents results from regressions of retail order imbalance by volume (in percentage) on the interaction of local climate change opinions measured with detailed questions. Panel A shows the regression results, and Panel B shows the summary statistics of the question scores. The question details are shown in Table A.1. The sample covers firm-incident pairs of both climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Personal	HarmUS	Consensus	FutureGen	HarmDev	Human	Governor	SupportRenew	TeachGW
Incident	1.923*	2.770**	1.625**	3.991**	3.060**	2.275*	2.465	6.398***	4.865**
	(1.034)	(1.362)	(0.771)	(1.655)	(1.332)	(1.226)	(1.527)	(2.278)	(2.265)
Incident × *Opinion*	-0.041*	-0.043**	-0.028**	-0.055**	-0.045**	-0.038*	-0.044*	-0.096***	-0.062**
	(0.021)	(0.021)	(0.013)	(0.022)	(0.019)	(0.020)	(0.026)	(0.034)	(0.028)
EA	0.801***	0.801***	0.803***	0.802***	0.802***	0.802***	0.998***	0.692***	0.750***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.260)	(0.180)	(0.247)
N	191643	191643	191643	191643	191643	191643	123931	148341	154986
R^2	0.111	0.111	0.111	0.111	0.111	0.111	0.086	0.118	0.104
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days								

Panel B: Summary Statistics

	Personal	HarmUS	Consensus	FutureGen	HarmDev	Human	Governor	SupportRenew	TeachGW
N	191,643	191,643	191,643	191,643	191,643	191,643	123,931	148,341	154,986
Mean	45.89	62.66	55.47	71.67	66.70	58.58	58.71	66.16	79.79
SD	6.34	6.32	9.49	5.53	6.92	6.18	5.06	4.00	4.27
Min	28.00	44.00	30.00	52.00	44.00	40.30	40.44	53.00	62.55
p25	40.85	58.07	48.93	68.49	62.09	54.77	55.51	63.50	76.89
p50	46.55	62.89	54.23	72.08	67.11	58.78	59.11	66.44	80.32
p75	50.92	67.29	61.94	75.31	71.25	62.66	62.42	69.01	83.16
Max	60.80	79.80	78.69	83.93	82.97	76.23	71.24	77.05	87.89

Table 6: Climate Incidents versus Other ES Incidents -
This table presents results from regressions of retail order imbalance by volume (in percentage) on the interaction of local climate change beliefs with the occurrence of climate risk incidents versus other E incidents and other S incidents. Columns (1) to (3) include both climate incidents and other ES incidents. Columns (4) to (6) report results in only other environmental incidents, excluding climate incidents. Columns (7) to (9) report results in only other social incidents, excluding climate incidents. These three samples' observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Belief	Concern		Belief	Concern		Belief	Concern
$Incident$	0.125	3.266**	2.345*						
	(0.112)	(1.537)	(1.247)						
$Incident \times Opinion$		-0.043**	-0.034*						
		(0.020)	(0.019)						
$Incident^{\text{Other E}}$	-0.207*	1.737	0.702	-0.174	1.766	0.730			
	(0.123)	(1.477)	(1.139)	(0.124)	(1.481)	(1.141)			
$Incident^{\text{Other E}} \times Opinion$		-0.027	-0.014		-0.027	-0.014			
		(0.020)	(0.018)		(0.020)	(0.018)			
$Incident^{\text{Other S}}$	0.116	-1.219	-0.542				0.158	-1.152	-0.487
	(0.136)	(1.563)	(1.227)				(0.138)	(1.561)	(1.226)
$Incident^{\text{Other S}} \times Opinion$		0.018	0.010					0.018	0.010
		(0.020)	(0.018)					(0.020)	(0.018)
EA	0.517***	0.516***	0.516***	0.275	0.275	0.275	0.209	0.210	0.209
	(0.154)	(0.154)	(0.154)	(0.195)	(0.195)	(0.195)	(0.218)	(0.218)	(0.218)
N	410336	410336	410336	108161	108161	108161	96845	96845	96845
R^2	0.109	0.109	0.109	0.120	0.120	0.120	0.085	0.085	0.085
Controls		Firm-Event FE, Seasonality (weekdays and months), Overlap days							

Table 7: Climate Incidents versus Other Characteristics

This table presents results from regressions of retail order imbalance by volume (in percentage) on the interaction of local climate change beliefs, controlling for interactions of other county-level variables, and IV estimates. Column (1) reports the results on how county-level variables affect retail order imbalance. Columns (2) and (3) show the main results after including the interactions of other county-level variables. Columns (4) and (5) report the estimates using the local educational attainment in 2010 to instrument for local opinions. First-stage F-statistics are reported at the bottom. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)
$Incident$	-1.617	2.550	1.772	2.986	2.822
	(1.422)	(2.265)	(2.067)	(3.169)	(3.122)
$Incident \times Belief$		-0.063**			
		(0.024)			
$Incident \times Concern$			-0.063***		
			(0.024)		
$Incident \times \hat{Belief}$				-0.069*	
				(0.041)	
$Incident \times \hat{Concern}$					-0.083*
					(0.050)
$Incident \times Population$	-0.060	-0.109	-0.092	-0.114	-0.103
	(0.073)	(0.077)	(0.076)	(0.090)	(0.087)
$Incident \times Income$	-0.008*	-0.001	0.001	0.000	0.004
	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)
$Incident \times White$	0.300	-0.451	-0.557	-0.529	-0.822
	(1.246)	(1.202)	(1.189)	(1.325)	(1.405)
$Incident \times Age$	0.052	0.056	0.056	0.057	0.057
	(0.051)	(0.049)	(0.049)	(0.049)	(0.049)
$Incident \times HouseValue$	0.002	0.003	0.004*	0.003	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$Incident \times HouseReturn$	-0.854	-0.885	-0.524	-0.888	-0.422
	(2.055)	(2.036)	(2.012)	(2.035)	(2.039)
EA	0.801***	0.801***	0.801***	0.801***	0.801***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	191643	191643	191643	191643
R^2	0.111	0.111	0.111		
F $statistics$				16.38	14.038
Controls	Firm-Incident FE, Overlap days				
	Seasonality (weekdays and months)				

Table 8: Heterogeneity Tests on Home Bias

This table shows results from regressions of retail order imbalance by volume (in percentage) on the interaction of local climate change beliefs with the occurrence of a climate risk incident and home bias characteristics. Four variables are used to measure home bias: $Ln(MV)$ is the natural logarithm of market values, $Ln(Counties\ Count)$ is the natural logarithm of the number of counties where a firm has establishments, $Ln(States\ Count)$ is the natural logarithm of the number of states where a firm has establishments, and HHI^{map} is the Herfindahl–Hirschman index of the firm's state-level establishments. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln(MV)		Ln(Counties Count)		Ln(States Count)		HHI^{map}	
Incident	52.405***	41.951***	12.202***	7.954**	13.150**	7.857**	-0.163	1.027
	(17.223)	(15.297)	(4.130)	(3.200)	(5.169)	(3.893)	(2.243)	(1.852)
Incident × *Home Bias*	-2.862***	-2.296***	-2.077**	-1.238*	-3.409**	-1.809	14.294*	6.742
	(0.959)	(0.856)	(0.886)	(0.713)	(1.660)	(1.288)	(7.348)	(5.643)
Incident × *Belief*	-0.697***		-0.163***		-0.177**		0.002	
	(0.227)		(0.055)		(0.070)		(0.030)	
Incident × *Belief* × *Home Bias*	0.038***		0.028**		0.046**		-0.191*	
	(0.013)		(0.012)		(0.022)		(0.099)	
Incident × *Concern*		-0.627***		-0.118**		-0.117**		-0.017
		(0.225)		(0.047)		(0.057)		(0.028)
Incident × *Concern* × *Home Bias*		0.034***		0.018*		0.027		-0.098
		(0.013)		(0.011)		(0.019)		(0.083)
EA	0.799***	0.799***	0.801***	0.801***	0.800***	0.800***	0.800***	0.800***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	191643	191643	191643	191643	191643	191643	191643
R^2	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111
Controls	Firm-Incident FE, Overlap days, Seasonality (weekdays and months)							

Table 9: Heterogeneity Results on Severity

This table presents results from regressions of retail order imbalance by volume (in percentage) on the triple interaction of local climate change beliefs with the occurrence of a climate risk incident and the severity of an incident. There are three ways to measure the severity: $I(Severity)$ is the most severe incident determined by Reprisk. $Pos.\Delta RRI$ is the Reprisk Index (RRI) change of a firm on an incident date. A higher RRI value represents a higher level of risk. I($Pos.\Delta RRI$) is a dummy variable equal to one when $Pos.\Delta RRI$ is higher than zero. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$I(Severity)$		I($Pos.\Delta RRI$)		$Pos.\Delta RRI$	
$Incident$	3.083**	2.282*	-1.748	-1.689	-0.433	-1.066
	(1.480)	(1.243)	(1.926)	(1.547)	(1.529)	(1.570)
$Incident \times Severity$	26.591**	25.831***	8.225***	6.881***	1.076***	1.023***
	(11.030)	(7.711)	(2.667)	(2.074)	(0.344)	(0.294)
$Incident \times Belief$	-0.042**		0.023		0.004	0.012
	(0.020)		(0.026)		(0.020)	(0.021)
$Incident \times Belief \times Severity$	-0.343**		-0.110***		-0.014***	
	(0.147)		(0.036)		(0.005)	
$Incident \times Concern$		-0.035*		0.025		
		(0.019)		(0.023)		
$Incident \times Concern \times Severity$		-0.373***		-0.103***		-0.015***
		(0.117)		(0.031)		(0.004)
EA	0.798***	0.797***	0.799***	0.798***	0.802***	0.800***
	(0.183)	(0.184)	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	191643	191643	191643	191643	191643
R^2	0.111	0.111	0.111	0.111	0.111	0.111
Controls	Firm-Incident FE, Overlap days					
	Seasonality (weekdays and months)					

Table 10: Robustness Tests on County Political Leanings

This table presents results on how local climate opinions affect retail order imbalance measured by volume (in percentage), controlling for the county-level political leanings. We measure a firm's local political leaning based on the counties where it headquarters or operates with the highest share of establishments in the incident year. A county has a democratic leaning if it voted for the Democratic Party in the most recent presidential election before a climate risk incident. *Blue* is the stock-market-participation weighted democratic-leaning county ratio, while $I(Blue)$ equals one when at least one county has a Democratic leaning. Columns (1) to (3) report results using *Blue* and Columns (4) to (6) report results using $I(Blue)$. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Incident	0.438	3.791**	2.893**	0.336	3.783**	2.878**	-0.057	3.060	2.409
	(0.310)	(1.760)	(1.420)	(0.339)	(1.614)	(1.321)	(0.099)	(1.876)	(1.545)
Incident × *Belief*		-0.052**			-0.053**			-0.042*	
		(0.026)			(0.023)			(0.025)	
Incident × *Concern*			-0.045*			-0.046**			-0.037
			(0.024)			(0.022)			(0.023)
Incident × *Blue*	-0.457	0.095	0.093						
	(0.312)	(0.384)	(0.390)						
Incident × $I(Blue)$				-0.317	0.150	0.155			
				(0.330)	(0.369)	(0.378)			
Incident × $I(Red)$							0.544*	0.171	0.163
							(0.282)	(0.333)	(0.326)
EA	0.803***	0.802***	0.801***	0.803***	0.802***	0.801***	0.804***	0.802***	0.802***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	191643	191643	191643	191643	191643	191643	191643	191643
R^2	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111	0.111
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days								

Table 11: Robinhood Results

This table reports results on the Robinhood firm-day sample, which includes firms in the RepRisk metrics dataset from early 2018 to late 2020. $Incident$, $Incident^{OtherE}$, and $Incident^{OtherS}$ are dummy variables equal to one if an incident happens. Columns (1) to (3) show the results on the user holding change in a three-day window centered by day t. Columns (4) to (6) show the results on the volatility of hourly user holding change observations in a three-day window centered by day t. Standard errors clustered by date are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta RI_{t-1,t+1}$			$\Delta RI\ Volatility_{t-1,t+1}$		
$Incident$	0.004	0.201***	0.176**	0.008	0.210***	0.180***
	(0.017)	(0.078)	(0.070)	(0.008)	(0.043)	(0.038)
$Incident \times Belief$		-0.003**			-0.003***	
		(0.001)			(0.001)	
$Incident \times Concern$			-0.003**			-0.003***
			(0.001)			(0.001)
$Incident^{Other\ E}$	-0.008	0.009	0.009	0.001	0.007	0.007
	(0.028)	(0.008)	(0.008)	(0.012)	(0.005)	(0.005)
$Incident^{Other\ S}$	-0.000	-0.005	-0.005	-0.002	-0.003	-0.003
	(0.012)	(0.009)	(0.009)	(0.006)	(0.005)	(0.005)
EA	0.006	0.059**	0.059**	-0.001	0.028**	0.028**
	(0.044)	(0.028)	(0.028)	(0.021)	(0.014)	(0.014)
N	1045241	904203	904203	1116032	965481	965481
R^2	0.013	0.032	0.032	0.047	0.076	0.076
Controls			Firm FE and Date FE			

Appendix for
"Does Climate Change Affect Retail Investors?
Your Opinion Matters"

A.1 Variable Definitions

Climate Change Opinions	
Opinion - Belief$_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"whether global warming is happening"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
Opinion - Concern$_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"How worried are you about global warming?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
Opinion - Belief(Major)$_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"whether global warming is happening"**. It is calculated based on counties where firm i has the three highest percentages of its establishments in year y according to NETS.
Opinion - Concern(Major)$_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"How worried are you about global warming?"**. It is calculated based on counties where firm i has the three highest percentages of its establishments in year y according to NETS.
Opinion - Belief(HQ)$_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"whether global warming is happening"**. It is calculated based on the county where firm i is headquartered in year y.
Opinion - Concern(HQ)$_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"How worried are you about global warming?"**. It is calculated based on the county where firm i is headquartered in year y.
Retail Trading	
Retail Imbalance (Volume)$_{i,e,t}$	A continuous variable defined as the buy-sell imbalance in volume of retail trades for the pair of firm i and event e on day t.
Retail Imbalance (Trade)$_{i,t}$	A continuous variable defined as the buy-sell imbalance in the number of retail trades for the pair of firm i and event e on day t.
Incident Dummies	
Incident$_{i,t}$	A dummy equal one if the date t is within one week (five trading days) of the firm-incident of climate risk incidents.
Incident$_{i,t}^{otherE}$	A dummy equal one if the date t is within one week (five trading days) of the firm-incident of other E incidents.

$\text{Incident}_{i,t}^{otherS}$	A dummy equal one if the date t is within one week (five trading days) of the firm-incident of other S incidents.
$\text{Incident}_{i,t}^{otherES}$	A dummy equal one if the date t is within one week (five trading days) of the firm-incident of other E or S incidents.
$\text{EA}_{i,t}$	A dummy equal one if the firm i day t is included in [-20, 20] trading days of firm i's earnings announcement window.
Other Variables	
$\text{Education}_{i,y}$	A continuous variable that measures the local educational attainment, defined as the percent of people 25 years or older who have a bachelor's degree or higher from the Census Bureau's American Community Survey (ACS) five-year estimates in 2010. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year of 2010.
$\text{Population}_{i,y}$	A continuous variable in millions that measures the total population of a county from the Census Bureau's Population and Housing Unit Estimates. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year y.
$\text{Income}_{i,y}$	A continuous variable defined as the per capita personal income in thousand dollars from the Bureau of Economic Analysis (BEA)'s Personal Income by County. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year y.
$\text{White}_{i,y}$	A continuous variable defined as the percent of the local population identified ethnicity as white from the Census Bureau's Population and Housing Unit Estimates in 2010. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year of 2010.
$\text{Age}_{i,y}$	A continuous variable defined as the median age of a county from the Census Bureau's Population and Housing Unit Estimates. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year of 2010.
$\text{HouseValue}_{i,y}$	A continuous variable measured the local house values based on the 2000 level from the Federal Housing Finance Agency (FHFA) annual county-level house price indices. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year y.
$\text{HouseReturn}_{i,y}$	A continuous variable measured the annual change of $\text{HouseValue}_{i,y}$. It is calculated based on the county where firm i has the highest percentage of its establishments and its headquarter county in year y.
$\text{Book/Market}_{i,y}$	A continuous variable measured the book-to-market ratio of a firm i in year y collected from WRDS Financial Ratios Suite.
$\text{ROA}_{i,y}$	A continuous variable measured the return on assets of a firm i in year y collected from WRDS Financial Ratios Suite.

$\text{Leverage}_{i,y}$	A continuous variable measured the total debts over total assets of a firm i in year y collected from WRDS Financial Ratios Suite.
$\text{Log(asset)}_{i,y}$	A continuous variable measured the natural logarithm of total assets of a firm i in year y collected from Compustat.
$\text{HHI}_{i,e}^{map}$	A continuous variable defined as the HHI index using a firm i's state-level establishment shares according to NETS in the year of the event e.
$\text{Num_County}_{i,e}$	A count variable defined as the number of unique counties where a firm i has establishments according to NETS in the year of the event e.
$\text{Num_State}_{i,e}$	A count variable defined as the number of unique states where a firm i has establishments according to NETS in the year of the event e.
$\text{I(Severity)}_{i,e}$	A dummy equal one if the firm i's event e has a severity score of three (out of three) in RepRisk.
$\text{Pos.}\Delta\ \text{RRI}_{i,e}$	A continuous variable defined as the Reprisk firm-level metrics increase on the day of firm i's event e.
$\text{I(Pos.}\Delta\ \text{RRI)}_{i,e}$	A dummy equal one if the $\text{Pos.}\Delta\ \text{RRI}_{i,e}$ is larger than zero.
Other Climate Change Beliefs	
$\text{Personal}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you think that global warming will harm you personally?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{HarmUS}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you think that global warming will harm people in the United States?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{Consensus}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **'Do you agree that most scientists think global warming is happening?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{FutureGen}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you think that global warming will harm future generations of people?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{HarmDev}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you think that global warming will harm people in developing countries?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.

$\text{Human}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you think that global warming is caused mostly by human activities?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{Governor}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you think your governor should be doing more or less to address global warming?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{SupportRenew}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you support that requiring utilities to produce 20% electricity from renewable sources?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
$\text{TeachGW}_{i,y}$	A continuous variable defined as the climate change belief measure based on the survey question **"Do you agree that schools should teach about global warming ?"**. It is calculated based on the county where firm i has the highest percentage of its establishments in year y according to NETS.
Robinhood Variables	
$\text{Incident}_{i,t}$	A dummy equal one if date t is the date of one climate risk incident for firm i.
$\text{Incident}_{i,t}^{otherE}$	A dummy equal one if date t is the date of one other E incident for firm i.
$\text{Incident}_{i,t}^{otherS}$	A dummy equal one if date t is the date of one other S incident for firm i.
$\text{EA}_{i,t}$	A dummy equal one if date t is the earnings announcement date for firm i.
$\Delta RI_{t-1,t+1}$	A continuous variable that measures the user holding from $t-1$ to $t+1$ for a firm and scaled by total asset as in Moss et al. (2024).
$\Delta RIvolatility_{t-1,t+1}$	A continuous variable that measures the volatility of hourly user holding count from $t-1$ to $t+1$ for a firm and scaled by total asset as in Moss et al. (2024).

A.2 Climate Change Incidents from RepRisk

Topic Tag	Definition and Issues
Greenhouse gas (GHG) emissions	Defined as greenhouse gases covered under the Kyoto Protocol include carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbon (PFCs), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3). They cause the issues of climate change and global pollution. This group of incidents do not include incidents caused by coal-fired power plants and drilling.
Greenhouse gas (GHG) pollution	Defined as greenhouse gases covered under the Kyoto Protocol include carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbon (PFCs), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3). They cause the issues of climate change and global pollution. This group of incidents do not include incidents caused by coal-fired power plants and drilling.
Coal-fired power plants	It includes power plants that generate energy by burning coal, which is a leading source of carbon-dioxide emissions. It is associated with issues, including toxic air and water pollution, human health concerns, and global warming.
Drilling	This category includes three sub-types of drilling: arctic drilling (petroleum exploration in Arctic geological basins), deep sea drilling (a process of drilling for oil and gas beneath the ocean floor), and off-shore drilling (a process of oil drilling beneath seabed rock formations). These activities result in several issues, such as, impacts on landscapes, ecosystems and biodiversity, and potential impact on wildlife in vulnerable areas such as endangered bird species, whales, and polar bears.

A.3 Appendix Figures

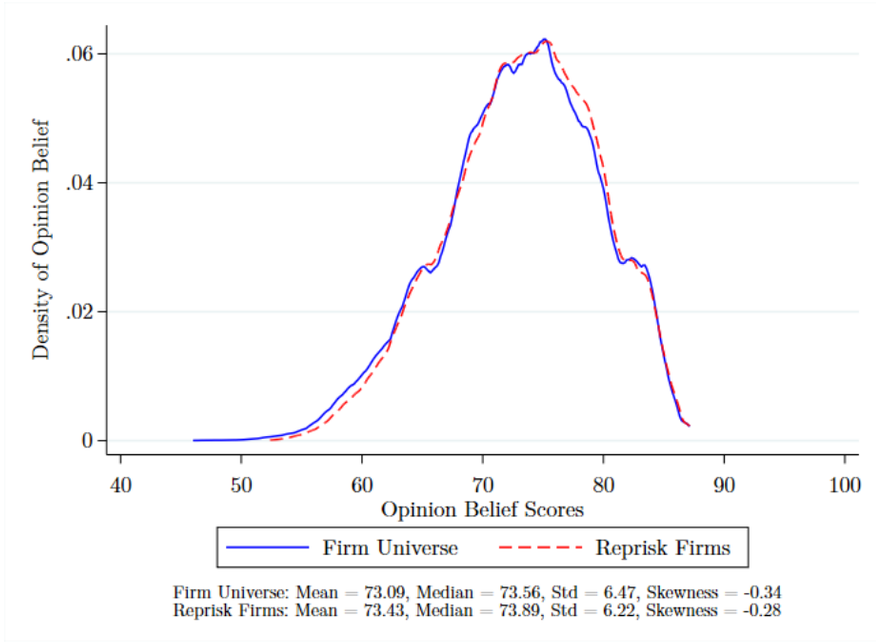
Figure IA.1: Climate Change Opinion - Belief
This figure plots the county-level "happening" scores in the Yale Climate Change Opinion Survey from 2014 to 2023.



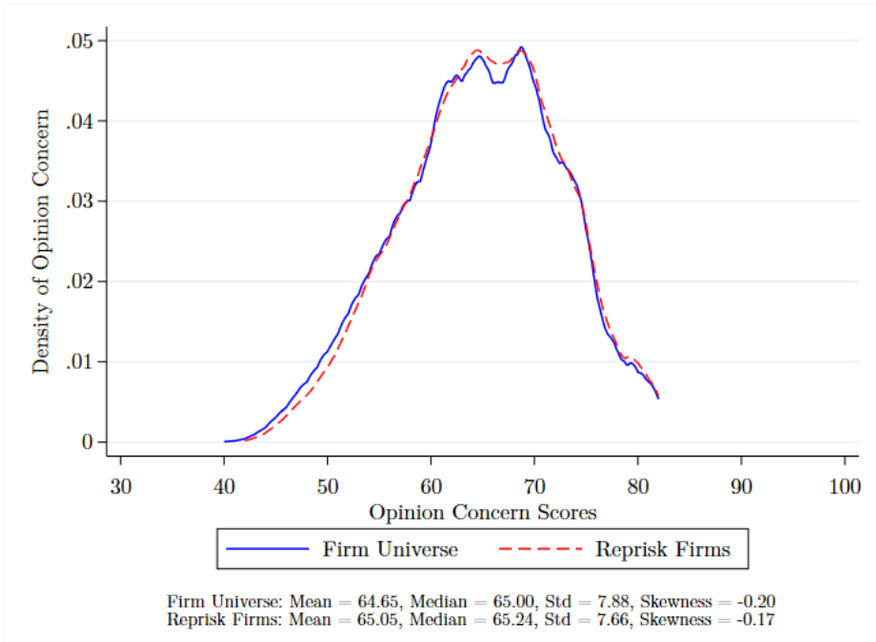
Figure IA.2: Climate Change Opinion - Concern
This figure plots the county-level "worried" scores in the Yale Climate Change Opinion Survey from 2014 to 2023.



Figure IA.3: Score Distribution
This figure plots the distribution of the climate change opinions, *Belief* in Panel A and *Concern* in Panel B, in the sample of the firm universe and Reprisk firm universe during 2014 and 2023. The firm universe includes firm-year pairs of all firms that have historical headquarter information in SEC 8-K filing while the Reprisk firm universe includes firm-year pairs of all firms that are covered by Reprisk with an Reprisk index (RRI).

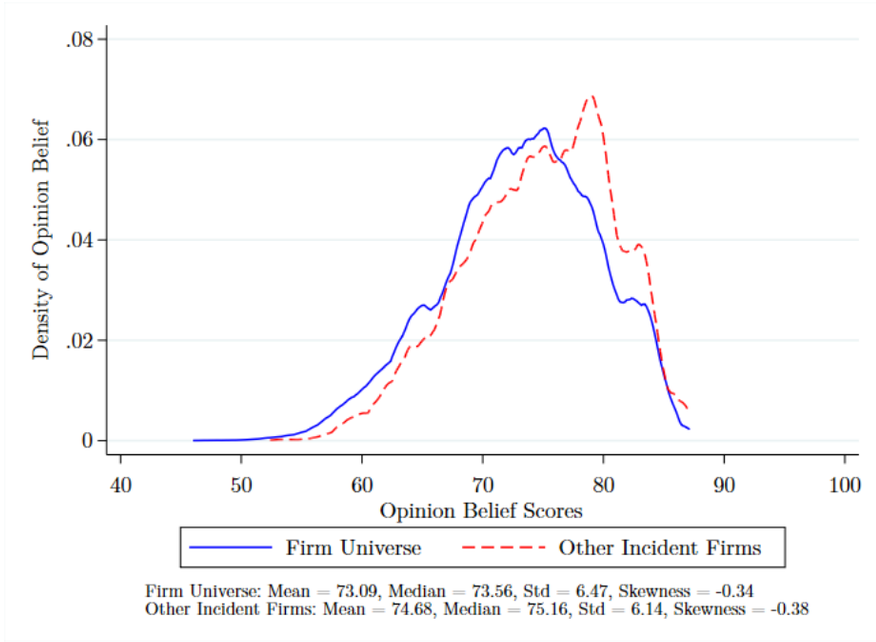


(a) Opinion Belief

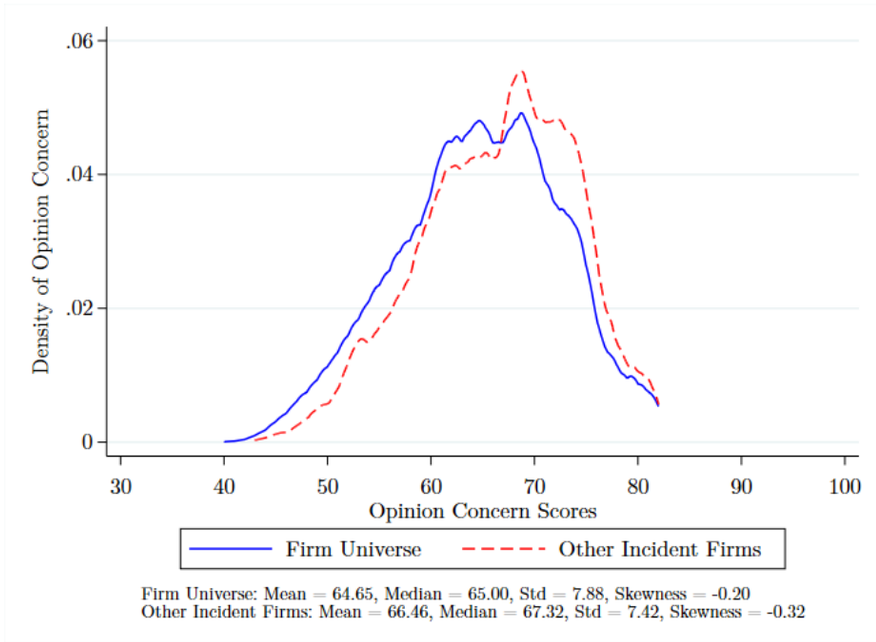


(b) Opinion Concern

Figure IA.4: Score Distribution
This figure plots the distribution of the climate change opinions, *Belief* in Panel A and *Concern* in Panel B, in the sample of the other E and S incidents and the sample of the firm universe during 2014 and 2023. The other incident sample includes firm-level other E and S incidents, while the firm universe includes firm-year pairs of all firms that have historical headquarter information in SEC 8-K filing.



(a) Opinion Belief



(b) Opinion Concern

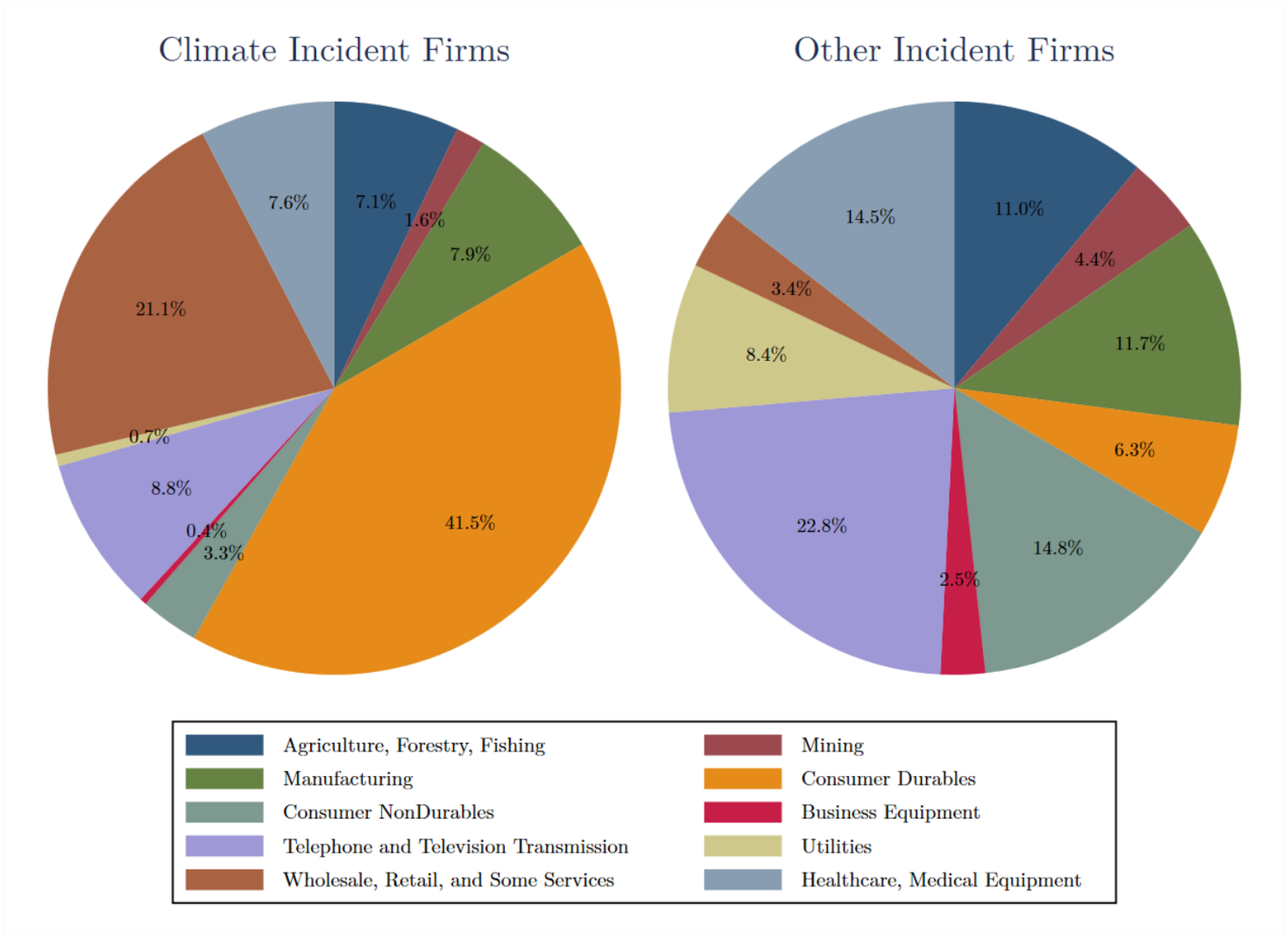


Figure IA.5: Industry Distribution
This figure shows the distribution of the firms' Fama-French 10 industry classification among climate incidents and other incidents in our sample.

A.4 Appendix Tables

Table IA.1: Firm-level Climate Change Opinion Measures in the Compustat firm sample
This table reports the summary statistics of climate change belief measures for the firm universe from 2014 to 2023. This sample includes all firms that have historical headquarter information in SEC 8-K filing. Panel A includes two sets of variables for *Belief* and *Concern*, following the definition in Eq. (1). Panel B provides the correlation matrix among these variables. All variables are defined in Table A.1.

Panel A: Climate Change Opinion Scores

	N	mean	sd	min	p25	p50	p75	max
Opinion Belief	31,539	73.09	6.47	46.00	69.00	73.56	77.85	87.15
Opinion Belief(Major)	31,540	72.71	5.67	46.00	69.00	73.00	76.67	87.15
Opinion Belief(HQ)	46,377	73.82	6.64	46.00	69.37	74.25	78.84	87.15
Opinion Concern	31,539	64.65	7.88	40.00	59.31	65.00	70.37	81.99
Opinion Concern(Major)	31,540	64.18	7.01	40.00	59.34	64.30	69.15	81.99
Opinion Concern(HQ)	46,377	65.40	8.20	40.00	59.94	65.65	71.31	81.99

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)
Opinion Belief	1					
Opinion Belief(Major)	0.908***	1				
Opinion Belief(HQ)	0.848***	0.830***	1			
Opinion Concern	0.926***	0.862***	0.796***	1		
Opinion Concern(Major)	0.842***	0.935***	0.775***	0.922***	1	
Opinion Concern(HQ)	0.798***	0.796***	0.930***	0.865***	0.852***	1

Table IA.2: Firm-level Climate Change Opinion Measures in the RepRisk firm sample.
This table reports the summary statistics of climate change belief measures for the RepRisk firm universe from 2014 to 2023. This sample includes all firms covered by Reprisk with an Reprisk index (RRI). Panel A includes two sets of variables for $Belief$ and $Concern$, following the definition in Eq. (1). Panel B provides the correlation matrix among these variables. All variables are defined in Table A.1.

Panel A: Climate Change Opinion Scores

	N	mean	sd	min	p25	p50	p75	max
Opinion Belief	15,381	73.52	6.25	52.40	69.28	74.00	78.13	87.15
Opinion Belief(Major)	15,381	73.00	5.30	55.00	69.51	73.27	76.72	87.15
Opinion Belief(HQ)	18,449	73.73	6.54	52.00	69.24	74.17	78.75	87.15
Opinion Concern	15,381	65.09	7.69	42.00	59.91	65.28	70.61	81.99
Opinion Concern(Major)	15,381	64.46	6.60	44.00	59.89	64.61	69.11	81.99
Opinion Concern(HQ)	18,449	65.21	8.02	42.00	59.77	65.45	71.06	81.99

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)
Opinion Belief	1					
Opinion Belief(Major)	0.777***	1				
Opinion Belief(HQ)	0.951***	0.722***	1			
Opinion Concern	0.930***	0.754***	0.884***	1		
Opinion Concern(Major)	0.735***	0.938***	0.684***	0.814***	1	
Opinion Concern(HQ)	0.892***	0.707***	0.931***	0.956***	0.762***	1

Table IA.3: Excluding Climate Incidents on Earnings Announcement Dates
This table presents results from regressions of retail order imbalance (in percentage) on the interaction of local climate change beliefs with the occurrence of a climate incident. To further reduce the impact of earnings announcements, in this sample, we remove all incidents that are disclosed on earnings announcement dates. The final sample covers firm-incident pairs of climate incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Columns (1) to (3) use retail trade volume to measure retail trading activities and Columns (4) to (6) use the number of retail trades. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Volume			Trade		
Incident	0.055	3.426**	2.769**	0.196*	2.748*	2.427**
	(0.106)	(1.561)	(1.304)	(0.106)	(1.435)	(1.149)
Incident × *Opinion Belief*		-0.046**			-0.035*	
		(0.021)			(0.019)	
Incident × *Opinion Concern*			-0.042**			-0.035**
			(0.019)			(0.017)
EA	0.830***	0.829***	0.828***	0.108	0.107	0.107
	(0.182)	(0.182)	(0.183)	(0.145)	(0.144)	(0.144)
N	189019	189019	189019	189019	189019	189019
R^2	0.111	0.111	0.111	0.341	0.341	0.341
Controls	Firm-Incident FE, Overlap days					
	Seasonality (weekdays and months)					

Table IA.4: The Relation Between Incidents and Opinions
This table presents how incidents may affect opinions in the county-year and firm-year level samples. Panel A reports the results on how current local climate change opinions affect the frequency of future climate incidents in counties where a firm with at least one climate incident is headquartered. Panel B reports similar results on firms that have at least one RepRisk incident during 2014 and 2023. Standard errors clustered by county in Panel A and by firm in Panel B are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A				
	(1)	(2)	(3)	(4)
	$Incident_{t+1}$			
$Belief$	-0.007	0.052		
	(0.044)	(0.079)		
$Belief_{t+1}$		-0.090		
		(0.082)		
$Concern$			-0.049	-0.016
			(0.039)	(0.071)
$Concern_{t+1}$				-0.048
				(0.075)
N	3384	3384	3384	3384
R^2	0.719	0.719	0.719	0.719
Controls	County FE, State * Year FE			

Panel B				
	(1)	(2)	(3)	(4)
	$Incident_{t+1}$			
$Belief$	-0.005	-0.010		
	(0.007)	(0.008)		
$Belief_{t+1}$		0.009		
		(0.008)		
$Concern$			-0.006	-0.010
			(0.006)	(0.007)
$Concern_{t+1}$				0.007
				(0.006)
N	9708	9689	9708	9689
R^2	0.883	0.883	0.883	0.883
Controls	Firm FE, Year FE			

Table IA.5: Summary Statistics of the Firm-Incident-Day Sample for Other ES Incidents
This table reports the summary statistics of the other E incident sample in Panel A and other S incident sample in Panel B at the firm-incident-day level from 2014 to 2023, including retail trading measures and climate change belief measures. All variables are defined in Table A.1.

Panel A: Other E Incidents								
	N	mean	sd	min	p25	p50	p75	max
Retail Imbalance(Volume)	313,043	-1.19	18.04	-100.00	-9.90	-0.72	7.70	100.00
Retail Imbalance(Trade)	313,043	3.27	16.05	-100.00	-5.27	3.23	11.95	100.00
Opinion - Belief	313,043	73.12	6.17	52.40	68.92	73.37	78.08	87.15
Opinion - Belief(Major)	313,043	72.25	5.19	55.81	69.17	72.53	76.09	84.92
Opinion - Belief(HQ)	313,043	73.61	6.45	52.40	69.00	74.22	78.81	87.15
Opinion - Concern	313,043	64.54	7.53	42.97	59.35	64.82	70.02	81.99
Opinion - Concern(Major)	313,043	63.87	6.38	45.00	59.88	64.21	68.44	81.99
Opinion - Concern(HQ)	313,043	64.85	7.86	42.97	59.45	65.19	71.06	81.99
EA	313,043	0.36	0.48	0.00	0.00	0.00	1.00	1.00

Panel B: Other S Incidents								
	N	mean	sd	min	p25	p50	p75	max
Retail Imbalance(Volume)	569,747	-0.80	16.66	-100.00	-8.04	-0.18	6.80	100.00
Retail Imbalance(Trade)	569,747	3.94	15.23	-100.00	-3.83	3.89	11.98	100.00
Opinion - Belief	569,747	75.65	6.21	52.40	71.36	76.24	80.27	87.15
Opinion - Belief(Major)	569,747	74.93	4.99	56.49	71.56	75.19	78.61	87.15
Opinion - Belief(HQ)	569,747	75.89	6.70	52.40	71.43	77.19	81.18	87.15
Opinion - Concern	569,747	67.54	7.37	43.00	62.35	68.39	73.13	81.99
Opinion - Concern(Major)	569,747	67.14	6.12	45.00	63.05	67.36	71.53	81.99
Opinion - Concern(HQ)	569,747	67.45	7.98	43.00	61.72	68.45	73.41	81.99
EA	569,747	0.34	0.47	0.00	0.00	0.00	1.00	1.00

Table IA.6: Summary Statistics of Firm Characteristics in Other ES sample
This table reports the summary statistics of firm characteristics in the year of incidents. Panel A reports the climate incident sample, Panel B includes other E incident sample, and Panel C reports the other S incident sample at the firm-incident level from 2014 to 2023. All variables are defined in Table A.1.

Panel A: Climate Incidents								
	N	mean	sd	min	p25	p50	p75	max
Book/Market	4,804	0.61	0.47	0.00	0.35	0.58	0.79	13.63
ROA	4,804	0.12	0.09	-0.79	0.07	0.11	0.16	0.84
Leverage	4,804	0.30	0.14	0.00	0.18	0.30	0.40	0.87
Log(asset)	4,804	10.83	1.56	4.22	9.86	10.98	12.38	13.38

Panel B: Other E Incidents								
	N	mean	sd	min	p25	p50	p75	max
Book/Market	7,940	0.50	0.45	0.00	0.19	0.42	0.69	7.44
ROA	7,940	0.13	0.08	-0.69	0.08	0.13	0.16	0.60
Leverage	7,940	0.33	0.15	0.00	0.22	0.32	0.43	0.78
Log(asset)	7,940	10.40	1.58	3.17	9.44	10.62	11.43	13.38

Panel C: Other S Incidents								
	N	mean	sd	min	p25	p50	p75	max
Book/Market	14,637	0.35	0.37	0.00	0.12	0.24	0.46	5.69
ROA	14,637	0.14	0.11	-1.58	0.09	0.14	0.18	0.91
Leverage	14,637	0.32	0.15	0.00	0.21	0.32	0.41	0.85
Log(asset)	14,637	10.51	1.64	0.18	9.42	10.60	11.81	13.38

Table IA.7: Distribution of Other ES Risk Incidents
This table reports the distribution of climate incidents in the main sample from 2014 to 2023. Panel A shows the distribution across four incident categories and Panel B lists the severity, reach and novelty of incidents defined by RepRisk.

Panel A: Distribution of Non-climate Incident			
E	S	Count	Percent (%)
0	1	15,954	65.61
1	0	2,831	11.64
1	1	5,532	22.75

Panel B: Distribution of Characteristics			
	Severity (%)	Reach (%)	Novelty (%)
1	69.65	39.68	64.83
2	27.73	36.72	35.17
3	2.62	23.60	–

Table IA.8: Determinants of Climate Change Opinion Measures
This table presents the determinants of opinions using county-year observations from 2014 to 2023. Column (1) reports the results on opinion-belief scores and Column (2) reports the results on opinion-worried scores from YCOM. County-level variables include a list of demographic and economic variables. *Education* is defined as the percent of people 25 years or older who have a bachelor's degree or higher in 2010. *Population* is the total population of a county in millions. *Income* is the per capita personal income in thousand dollars. $White$ is defined as the percent of the local population identified ethnicity as white in 2010. *Age* is defined as the median age of a county in 2010. $HouseValue$ and $HouseReturn$ measure the local house values and their annual changes. Standard errors double clustered by county and year are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)
	Belief	Concern
Education	0.413***	0.366***
	(0.024)	(0.028)
Population	0.893**	1.197***
	(0.370)	(0.361)
Income	-0.018*	-0.008
	(0.009)	(0.008)
$White$	-14.938***	-17.979***
	(1.035)	(1.063)
Age	0.193***	0.172***
	(0.019)	(0.020)
$HouseValue$	0.004	0.011***
	(0.003)	(0.003)
$HouseReturn$	1.084	-1.952
	(1.616)	(1.442)
N	23449	23449
R^2	0.628	0.660
Controls	Year FEs	

Table IA.9: Heterogeneity Results on Novel and Severe Incidents
This table presents results from regressions of retail order imbalance (by volume and in percentage) on the novelty and severity of a climate risk incident. The novelty of an incident is one if this issue is re-occurring and two if this issue is new for this firm, while the severity of an incident measures the impact, with three being the most severe. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
	Belief		Concern	
$Incident$	3.107	4.232**	3.051*	4.248**
	(1.979)	(2.128)	(1.791)	(1.791)
$Incident \times Opinion$	-0.041	-0.055*	-0.046*	-0.063**
	(0.026)	(0.028)	(0.027)	(0.027)
$Incident \times (Novelty = 2)$	1.168		-0.555	
	(2.619)		(2.168)	
$Incident \times Opinion \times (Novelty = 2)$	-0.017		0.008	
	(0.035)		(0.033)	
$Incident \times (Novelty = 1 \ \& \ Sev = 2)$		-3.655		-3.981
		(4.478)		(3.939)
$Incident \times (Novelty = 1 \ \& \ Sev = 3)$		9.022		11.521
		(10.573)		(8.591)
$Incident \times (Novelty = 2 \ \& \ Sev = 1)$		-0.993		-1.663
		(3.638)		(2.702)
$Incident \times (Novelty = 2 \ \& \ Sev = 2)$		-0.369		-3.468
		(3.845)		(2.924)
$Incident \times (Novelty = 2 \ \& \ Sev = 3)$		37.919***		31.686***
		(11.559)		(8.252)
$Incident \times Opinion \times (Novelty = 1 \ \& \ Sev = 2)$		0.043		0.054
		(0.060)		(0.059)
$Incident \times Opinion \times (Novelty = 1 \ \& \ Sev = 3)$		-0.110		-0.160
		(0.141)		(0.128)
$Incident \times Opinion \times (Novelty = 2 \ \& \ Sev = 1)$		0.015		0.027
		(0.048)		(0.040)
$Incident \times Opinion \times (Novelty = 2 \ \& \ Sev = 2)$		-0.003		0.044
		(0.053)		(0.045)
$Incident \times Opinion \times (Novelty = 2 \ \& \ Sev = 3)$		-0.502***		-0.469***
		(0.157)		(0.129)
EA	0.801***	0.792***	0.802***	0.792***
	(0.183)	(0.183)	(0.183)	(0.184)
N	191643	191643	191643	191643
R^2	0.111	0.111	0.111	0.111
Controls	Firm-Incident FE, Overlap days			
	Seasonality (weekdays and months)			

Table IA.10: Heterogeneity Results on Widespread and Severe Incidents
This table presents results from regressions of retail order imbalance (by volume and in percentage) on the spread and severity of a climate risk incident. The reach of an incident captures how far the information source reaches readers in terms of readership and circulation, with three being the high reach. The severity of an incident measures the impact, with three being the most severe. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
	Belief		Concern	
Incident	4.881**	5.653**	3.037*	4.276**
	(2.111)	(2.238)	(1.709)	(1.678)
Incident × *Opinion*	-0.064**	-0.070**	-0.044*	-0.058**
	(0.028)	(0.030)	(0.026)	(0.025)
Incident × (*Reach* = 2)	-2.673		-0.214	
	(2.950)		(2.282)	
Incident × (*Reach* = 3)	-1.615		-0.389	
	(4.483)		(3.704)	
Incident × *Opinion* × (*Reach* = 2)	0.031		-0.003	
	(0.040)		(0.035)	
Incident × *Opinion* × (*Reach* = 3)	0.022		0.006	
	(0.060)		(0.055)	
Incident × (*Reach* = 1 & *Sev* = 2)		-1.585		-3.218
		(4.329)		(3.496)
Incident × (*Reach* = 1 & *Sev* = 3)		22.047		37.142**
		(24.656)		(17.378)
Incident × (*Reach* = 2 & *Sev* = 1)		-3.990		-1.236
		(2.978)		(2.195)
Incident × (*Reach* = 2 & *Sev* = 2)		-6.023		-4.784
		(5.438)		(3.755)
Incident × (*Reach* = 2 & *Sev* = 3)		30.423**		24.687***
		(11.948)		(7.976)
Incident × (*Reach* = 3 & *Sev* = 1)		-2.145		-1.567
		(4.910)		(4.220)
Incident × (*Reach* = 3 & *Sev* = 2)		-2.564		-0.822
		(6.337)		(4.582)
Incident × (*Reach* = 3 & *Sev* = 3)		11.630		6.130
		(11.524)		(8.011)
Incident × *Opinion* × (*Reach* = 1 & *Sev* = 2)		0.010		0.037
		(0.059)		(0.053)
Incident × *Opinion* × (*Reach* = 1 & *Sev* = 3)		-0.294		-0.562**
		(0.341)		(0.274)
Incident × *Opinion* × (*Reach* = 2 & *Sev* = 1)		0.046		0.009
		(0.040)		(0.033)
Incident × *Opinion* × (*Reach* = 2 & *Sev* = 2)		0.067		0.057
		(0.074)		(0.057)
Incident × *Opinion* × (*Reach* = 2 & *Sev* = 3)		-0.407**		-0.370***
		(0.159)		(0.121)
Incident × *Opinion* × (*Reach* = 3 & *Sev* = 1)		0.024		0.019
		(0.065)		(0.062)
Incident × *Opinion* × (*Reach* = 3 & *Sev* = 2)		0.028		0.006
		(0.084)		(0.068)
Incident × *Opinion* × (*Reach* = 3 & *Sev* = 3)		-0.124		-0.057
		(0.151)		(0.111)
EA	0.802***	0.791***	0.801***	0.791***
	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	191643	191643	191643
R^2	0.111	0.111	0.111	0.111
Controls	Firm-Incident FE, Overlap days Seasonality (weekdays and months)			

Table IA.11: Robustness: Excluding oil firms

This table presents results from regressions of retail order imbalance (in percentage) on the interaction of local climate change beliefs with the occurrence of a climate risk incident. The sample excludes oil-related firms, whose SIC codes are 1311, 1381, 1382, 2911, or 5171. It covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Panel A uses retail trade volume and Panel B uses retail trade numbers. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: Retail Imbalance (Volume)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Belief			Concern		
Incident	0.176	5.952***	4.045*	4.870**	4.547**	3.881**	3.698**
	(0.147)	(2.289)	(2.402)	(2.032)	(1.777)	(1.754)	(1.577)
Incident × *Opinion*		-0.078***			-0.067**		
		(0.030)			(0.026)		
Incident × *Opinion*(*Major*)			-0.053*			-0.058**	
			(0.032)			(0.026)	
Incident × *Opinion*(*HQ*)				-0.063**			-0.054**
				(0.026)			(0.023)
EA	0.565**	0.559**	0.562**	0.560**	0.556**	0.558**	0.557**
	(0.220)	(0.219)	(0.219)	(0.220)	(0.220)	(0.220)	(0.220)
N	112605	112605	112605	112605	112605	112605	112605
R^2	0.091	0.091	0.091	0.091	0.091	0.091	0.091
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days						

Panel B: Retail Imbalance (Trade)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Belief			Concern		
Incident	0.247*	4.779**	5.013**	4.151**	3.938**	3.953**	3.347**
	(0.146)	(2.030)	(2.078)	(1.940)	(1.556)	(1.540)	(1.467)
Incident × *Opinion*		-0.061**			-0.057**		
		(0.027)			(0.023)		
Incident × *Opinion*(*Major*)			-0.066**			-0.058**	
			(0.028)			(0.023)	
Incident × *Opinion*(*HQ*)				-0.053**			-0.047**
				(0.025)			(0.021)
EA	0.146	0.141	0.141	0.141	0.138	0.139	0.139
	(0.212)	(0.212)	(0.212)	(0.212)	(0.212)	(0.212)	(0.212)
N	112605	112605	112605	112605	112605	112605	112605
R^2	0.286	0.286	0.286	0.286	0.286	0.286	0.286
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days						

Table IA.12: Robustness Tests on County Political Leanings

This table presents subsample results on how local climate opinions affect retail order imbalance measured by volume (in percentage) based on county-level political leanings. We measure a firm's local political leaning based on the county with its most establishments in the incident year. Red counties are counties which voted for the Republican in the most recent presidential election outcome before a climate risk incident. Blue counties are counties which voted for the Democratic in the most recent presidential election outcome before a climate risk incident. The sample covers firm-incident pairs of climate risk incidents from 2014 to 2023, and observations are at the Firm-Incident-Day level on days -20 to +20 around each Firm-Incident. Columns (1) to (2) report results in the subsample of Republican counties and Columns (3) to (4) report results in the subsample of Democratic counties. Standard errors double clustered by firm and incident are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
	Red Counties		Blue Counties	
Incident	10.11**	9.026**	3.012*	2.682*
	(4.075)	(3.685)	(1.726)	(1.467)
Incident × *Belief*	-0.146**		-0.0404*	
	(0.0611)		(0.0228)	
Incident × *Concern*		-0.151**		-0.0405*
		(0.0635)		(0.0217)
EA	0.910**	0.904**	0.835***	0.835***
	(0.358)	(0.359)	(0.191)	(0.191)
N	40061	40061	168845	168845
R^2	0.100	0.101	0.117	0.117
Controls	Firm-Incident FE, Overlap days			
	Seasonality (weekdays and months)			