Are Retail Investors Penalizing Dirty Energy?*

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Abstract

We examine how retail investors' opinions about renewable energy and climate change shape investment behavior in energy finance. Using a decade of U.S. county-level survey data, we construct novel firm-level measures that capture retail investors' energy- and global-warming-related opinions. We find that, following the disclosure of firm-level dirty energy incidents, firms experience a significant decline in retail net demand when their retail investors are supportive of renewable energy, believe in global warming, or are concerned about climate change. This pattern is evident in both marketable retail orders from TAQ and user records from Robinhood Markets. In contrast, we do not find a comparable effect of these opinions for incidents that are risky but unrelated to energy activities. The results are not driven by local demographic characteristics, regulatory stringency, or political leanings. Overall, our findings suggest that energy finance is meaningfully influenced by investor views on energy and climate.

JEL Classifications: G12, G41, G51

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1 Introduction

Dealing with capital allocation to produce, transport, and consume energy, investors are facing the dual challenge of financing enough energy versus financing cleaner energy. At the heart of the energy transition debate, this tradeoff could subjectively depend on views about renewable energy and climate change. These views vary widely across investors, especially the broad base of retail investors. In a polarized U.S. society, it has become increasingly critical to understand how divergent investor opinions on these subjects shape their investment toward energy-related activities.[1] Through the lens of firm-specific dirty energy incidents, we examine this question by linking retail investor opinions to their trading behavior. We conjecture that retail investors' decisions following such incidents are shaped by their views on energy and climate change.

Identifying retail investors' opinion to the firm level is empirically challenging. We start by capturing local opinions using annual county-level data derived from the large national survey "Climate Change in the American Mind". Conducted twice a year, the survey is led by the Yale Program on Climate Change Communication since 2014 to construct the Yale Climate Opinion Map (YCOM).[2] This dataset is widely recognized in environmental economics and policy research and has been increasingly applied in recent climate finance studies.[3] We focus on the responses in each continental US county to three key questions: "How much do you support requiring utilities to produce electricity from renewable sources?", "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 "support for renewable energy", the second and third ones are to measure "belief" and "risk perception" of climate change,

[1]The ESG literature, with a broader but arguably ambiguous focus on sustainability and social issues, 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).

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

[3]See, 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); Bakkensen, Phan, and Wong (2025).

respectively.

Next, following the assumption of local bias in retail investment (e.g., Hirshleifer, Peng, and Wang, 2024), we link opinion data to firms through their geographic footprints. In the stock market context, extensive evidence reveals that investors, especially retail investors, tend to favor local firms, and that this bias is more pronounced for smaller firms or those with regional operations, which therefore rely more heavily on local investors.[4] To operationalize this notion, we treat retail investors from a firm's headquarter and top operating locations as representatives 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. We also account for substantial regional variation in stock market participation, which affects the representativeness of local investors (Hong, Kubik, and Stein, 2004). Following Lin (2020) with the Statistics of Income data from the IRS, we apply the stock market participation measure to weight local opinions. This approach allows us to finally construct time-varying measures of energy and climate 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. We utilize the RepRisk database which tracks negative ESG-related news about firms. Based on the detailed event descriptions in RepRisk, we focus specifically on dirty energy incidents which include negative news related to coal-fired power usage, various drilling activities, greenhouse gas (GHG) emissions and pollution. These incidents are closely tied to the usage of traditional fossil fuels and have worsen global warming and caused major pollution and health damage. Over 60% of firms involved in these incidents belong to either the energy or utilities sector. To measure firm-level retail net trading demand for the cross-section of firms in our tests, we construct a measure of retail order imbalances using the retail trading algorithm proposed by Boehmer, Jones, Zhang, and Zhang (2021) and modified by Barber, Huang, Jorion, Odean,

[4]See more evidence of the local bias of stock investment in Coval and Moskowitz (1999); Benartzi (2001); Ivković and Weisbenner (2005); Chi and Shanthikumar (2017); Branikas, Hong, and Xu (2020), etc.

and Schwarz (2024) with trade-level TAQ data. We also use data from Robinhood Markets Inc. to construct alternative measures of retail investor trading activities.

Applying the final matched sample of TAQ retail trading with dirty energy incidents from 2014 to 2023, we first find that, without considering investor opinions, there is no significant change in the average retail investor's trading when facing dirty energy incidents.[5] Our main focus then is to explore whether, and to what extent, the heterogeneity in energy and climate opinions affects retail trading behavior. With the inclusion of these opinion measures, we find that pro-renewable-energy or pro-climate opinions negatively affect retail trading of dirty energy firms. For example, following the disclosure of dirty energy incidents, retail investors' support for renewable energy would cause an average reduction in retail net demand of 6.54% of the firm's daily trading volume, which is quantitatively and qualitatively comparable to the average effect of important financial information, such as earnings announcements, on retail trading. The average effects of beliefs and concerns about climate change on retail investment are of similar magnitude. These results are robust to alternative definitions of the firm-level retail investor base, whether we proxy it using only the headquarters county or expand it to include additional operating counties.

Further analyses draw the economic implication that a firm with dirty energy incident disclosure would suffer net selling by retail investors when, on average, more than 66.8% of its retail investors support renewable energy, more than 74.0% believe in global warming, or more than 66.6% worry about global warming. Mapping these thresholds onto the Yale Climate Change Map, we find only fewer than 33.1% of counties in the U.S. mainland met these thresholds in 2014, whereas more than 50.3% did so by 2023. This contrast highlights the potential effect of the substantial rise in related public opinions on energy finance over the past decade. Applying more granular data from the Yale Program on Climate Change Communication, we also find that retail investor behavior is influenced by pro-climate opinions across multiple dimensions, which include (1) egoistic concerns–such as

[5]This finding is consistent with Moss, Naughton, and Wang (2024) that retail investors, on average, do not respond to ES-related signals.

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) support government and school initiatives to combat global warming.

A related omitted variable concern is that the energy and climate opinion measures might simply proxy for retail investors' overall risk aversion, thereby affecting retail reaction to risky incidents. To address this possible issue, we conduct a wide range of placebo tests by testing other risky incidents disclosed in RepRisk that are unrelated to dirty energy activities. If our findings are essentially driven by retail investors' general risk aversion, we would expect to observe a similar change in retail trading on firms following these other risky incidents. In contrast, we find that energy and climate opinion measures do not affect retail trading in these settings. Moreover, our main results remain robust after controlling for lagged and contemporaneous stock returns, suggesting that general risk aversion to risky financial signals is not the main force driving our findings. In addition, we control for the demographics of the retail investor representative base and apply education as an instrumental variable for energy and climate opinions to further alleviate the concern of omitted variables related to retail investors' risk aversion.

One alternative explanation for our results is that they may simply reflect the effects of local political polarization, which is related both to investor opinions and to policies and regulations. For example, firms experiencing dirty energy incidents in areas with pro–renewable-energy or pro–climate views may also face higher regulatory risk for energy activities, which could contribute to the observed decline in retail investor demand. To address this concern, we conduct robustness tests that control for the local political leaning of the representative retail investor base, helping to alleviate worries that our estimates are primarily driven by political polarization or differences in local energy and climate policy stringency.

Another concern is that our measure of energy or climate opinions may also capture the views of other stakeholders (e.g., officers, directors, employees) who reside in firms' major locations. Following a negative energy incident, firms with pro-renewable-energy or

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, as 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 do not find evidence that energy or climate opinions are informative for the disclosure of future dirty energy incidents at either the firm or county level, which mitigates concerns about reverse causality driving our results.

Additional heterogeneity tests show that our main result is amplified by the severity of dirty energy incidents. We also document substantial heterogeneity in the effects across firms' geographic layout, firm size, and the number of operating counties or states. Specifically, the influence of energy and climate opinions on retail trading in dirty energy firms is stronger for smaller firms and for firms with more geographically concentrated operations that span fewer counties or states. This pattern is consistent with the local-bias assumption underlying our construction of opinion measures and suggests that our findings are more pronounced for firms that are more likely to be the focus of locally biased retail investors.

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 energy and climate opinions influence this subgroup of retail investors, who are more likely to be younger and newer to investing.[6] Our findings show that all three opinion measures reduce the activeness and the growth of Robinhood users holding firms associated with dirty energy incidents. In contrast, when these opinions are not considered, the disclosure of dirty energy incidents does not significantly affect the activities of Robinhood users holding these firms. These results align with our findings from TAQ data. Overall, they suggest that dirty energy incidents followed by a deterioration in retail investor activity only when they support renewable energy, believe in or are highly concerned about global warming.

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

It is worth noting that, to assess the robustness of our findings, we rule out other firm-specific financial news overlapping with the climate-risk incident window like earnings announcements, as well as any factors that are constant within a firm-incident window, including the firm's industry or its recent operational and 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 contribute to the nascent literature on financing energy transition, which has largely focused on innovative financing programs for households, such as clean-energy-related residential loans (Bellon, LaPoint, Mazzola, and Xu, 2024) or auto loans (Bena, Bian, and Tang, 2023), and for corporations, such as green bonds (Flammer, 2021) or sustainability bank loans (Kim, Kumar, Lee, and Oh, 2025). To the best of our knowledge, ours is the first study to specifically link retail divestment to negative energy-related activities and their views on clean energy.

Our paper also relates to the growing literature that empirically examines retail investors' motivations for sustainability 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, Kölbel, Paetzold, and Zeisberger, 2023). Giglio, Maggiori, Stroebel, Tan, Utkus, and Xu (2024) conducted a one-and-half-year survey of Vanguard clients, highlighting the significance of both pecuniary and non-pecuniary motives. Focusing on energy finance, our study specifically examines retail investors' perceptions of renewable energy and global warming. We considers investor participation beyond limited sustainable investments in ESG or SRI funds to the broader stock universe involving dirty energy activities. In addition, we adopt an event-study framework and leverage long-term archival data, providing a broader perspective on retail investor behavior.

Our work can be broadly linked to research on the relevance of environmental and social

signals to retail investors, which has discovered mixed evidence. For example, retail investors have been shown to act on extreme weather events (Choi, Gao, and Jiang, 2020; Liu, Zhang, Zhang, and Li, 2023; Yu, 2023); they also trade on financially material ESG news (Li, Watts, and Zhu, 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, Naughton, and Wang, 2024). Our findings highlight the important role played by energy and climate opinions in energy finance, which encompass both pecuniary and nonpecuniary motives.

2 Empirical Measures and Sample Construction

To assess how the retail investors' response to dirty energy is affected by their energy and climate opinions, we need to construct a dataset composed of three different aspects. The first aspect captures the disclosure of companies' dirty energy incidents. The second aspect identifies firm-level retail investors 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 Dirty Energy Incidents

We rely on RepRisk to identify firm-level negative news that are directly linked to energy activities. 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 a sustainability or social risk incident. Once an incident is identified, RepRisk analysts conduct additional filtering and analyses to verify the issue, remove duplicates, and classify the nature of the incident into detailed categories.

This dataset of negative ESG incidents with daily granularity serves well for our study.[7] 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 or discretionary disclosures. Meanwhile, positive events are less likely to be reported in the media and more likely to be self-reported.

To further zoom in on incidents that are directly linked to energy activities, we focus on the following types of incidents according to RepRisk's issue tag definitions: drilling (including arctic drilling, deep sea drilling, and offshore drilling), coal-fired power plants, and greenhouse gas (GHG) emissions and pollution. These activities are closely tied to the usage of traditional fossil fuels (oil, natural gas, and coal) and have worsened global warming and caused major pollution or health damage.[8] As shown in Panel (a) of Figure 1, over 60% of firms involved in dirty energy incidents belong to either the energy sector (oil, gas, and coal extraction and products) or the utilities sector, which together constitute the core focus of energy finance. Panel (b) also reports the annual number of dirty energy incidents from 2014 to 2023. We observe a general upward trend in incident frequency through 2021, followed by a downward trend in the most recent years.

[Figure 1 here]

As presented in Panel A of Table 1, each dirty energy incident might involve multiple issue tags which are not assigned exclusively. For each event, RepRisk also measures degrees of its severity, reach, and novelty, ranging from 1 to 3 (or up to 2 for novelty) in ascending order of 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% of dirty

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

[8] The detailed definitions of these energy topic tags from RepRisk documentation are listed in Appendix A.2.

energy incidents are severe, around 32% are medium severe, and 2.79% are considered very severe. The reach variable measures how widespread the information source is, according to its readership and circulation. Around 49% of dirty energy 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 dirty energy incident sample, new issues and re-occurring issues are relatively evenly distributed, accounting for 42.73% and 57.27% respectively.

[Table 1 here]

2.2 Local Opinions towards Energy and Climate

We use the Yale Climate Opinion Map (YCOM) data to capture local opinions on renewable energy and 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 YCOM then depicts the percentage of American adults who hold particular beliefs, attitudes, and policy preferences about global warming, which has been recognized as the primary driver and most direct evidence of climate change. 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.[9] 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, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020; Addoum,

[9]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.

Ng, and Ortiz-Bobea, 2023; Dursun-de Neef and Ongena, 2023; Goldsmith-Pinkham et al., 2023).[10]

Applying the county-level survey results in the YCOM, we focus on the responses to three key questions related to energy activities: "How much do you support requiring utilities to produce electricity from renewable sources?", "Do you think global warming is happening?" and "How worried are you about global warming?", all starting in 2014.[11] Based on the survey design, the first question is to measure "support for renewable energy", the second and third questions are to measure "belief" and "risk perception" of climate change. We therefore name them as "**energy**", "**belief**" and "**concern**", respectively, which comprehensively measure public opinions toward energy and climate change. By leveraging YCOM's localized estimates, we capture nuanced geographic variations in climate attitudes across the United States. Appendix Figures IA.1 to IA.3 map the county-level values of these three measures across years in our sample. Although all public opinions on energy or global warming display geographical differences across the country, they have also 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 energy and climate 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.[12] We also consider the substantial regional variation in stock market participation (Hong, Kubik, and Stein, 2004), which could affect the representativeness of local investors. Following Lin (2020), we measure a county's stock market participation by

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

[11]The YCOM ended the survey of "How much do you support requiring utilities to produce electricity from renewable sources?" in 2021.

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

the ratio of its aggregate dividend income over adjusted gross income ($Div\ ratio$), using the 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 investor energy and climate opinion measures 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 highest share of establishments in year y.[13] 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 energy and climate in each county, measured in "**energy**", "**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 energy and climate opinion measures for retail investors in the matched firm-incident sample with RepRisk dirty energy incidents from 2014

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

to 2023. As shown in Panel A, the average *Energy* score is 66.09, which means that, for an average dirty energy firm, 66.09% of the population in its representative retail investor base counties support renewable energy. This score averages 65.27 if we consider a firm's broader geographical presence and 66.72 based on its headquarter county. For such an average firm, 71.61% to 73.83% of the population in its representative retail investor base counties believe in global warming, and 63.30% to 65.11% worry about global warming. These *Belief* and *Concern* scores have slightly higher standard deviations than the *Energy* scores but follow similar distribution patterns. The wide range from minimum to maximum values of these scores also indicates substantial variation in energy and climate opinions across firms. Such divergence provides an ideal empirical setting to capture heterogeneity in retail opinions for testing our research questions. In Panel B, the high correlations within the group of *Energy*, *Belief*, or *Concern* show that different versions of each opinion measure are significantly correlated. Plus, *Energy*, *Belief*, and *Concern* are also highly correlated, suggesting that populations who support renewable energy largely overlap with those who believe in and are concerned about global warming.

[Figure 2 here]

A possible concern is that the matched sample in Table 2 might be subject to selection bias, potentially leading to limited variation in these opinions. However, as shown in Figure 2, the distributions of *Energy*, *Belief*, and *Concer* are similar between the dirty energy incident firm sample and the broader set of firms with historical headquarter information in SEC 8-K filings, although the dirty energy incident sample exhibits a slightly higher lower bound and thus a shorter left tail. Alternatively, untabulated comparisons with the Compustat firm universe or the RepRisk firm universe also show a similar alignment. These comparisons alleviate concerns that dirty energy firms are systematically biased in terms of retail investors' energy and climate opinions. Additionally, Figure 3 provides snapshots of the YCOM map at the beginning, the midpoint, and the end of our sample period, with the major locations (footprint and headquarter) of dirty energy firms highlighted in red

boundaries. It reveals that, over the years, these dirty energy firms of our interest have a broad geographic distribution across regions with high to low energy or climate opinions.

[Figure 3 here]

2.3 Retail Investor Trading

To capture retail trading, we adopt the methods developed by Boehmer et al. (2021) and modified by Barber et al. (2024) using TAQ data. To estimate net retail demand at the individual stock level, we follow them to define daily retail order imbalances for each stock as the difference between daily retail purchase volume and daily retail sell volume, scaled by total retail trading volume.

Additionally, we complement our main analysis by testing a specific sample of retail investors: those using the Robinhood trading platform.[14] 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 holdings is relatively short (from May 2018 to August 2020) and only provides the count of users without detailed ownership information, it could provide supplemental evidence of how energy and climate opinions influence retail investor trading.

2.4 Other County-level Data

To capture the effect of county demographics and economic development on energy and climate opinions of local investors and their trading activities, we include a list of county-level variables and estimate the impact of energy and climate 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. Educational attainment is measured using the Census Bureau's American Community Survey (ACS) five-year estimates. Besides these

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

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 County 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, following the approach in Lin (2020), we select the year 2010, which is the latest data available year earlier than our sample period, and construct $Education$, Age, and $White$ as static values throughout the sample.

2.5 Sample Description

Starting with dirty energy incidents from 2014 to 2023 of U.S. public firms matched with retail opinions, we exclude financial firms (SIC codes between 6000 and 6999) and link the rest to COMPUSTAT and TAQ. The final sample comprises 1,487 unique dirty energy incidents across 495 unique firms, resulting in 5,024 firm-incident observations. Following Li, Watts, and Zhu (2024), we apply a [-20, +20] trading-day window around each incident date, yielding a final test sample of 191,643 Firm-IncidentDate-Day observations.

[Table 3 here]

As shown in Table 3, the average net retail demand measured as retail trading volume imbalance is -1.68%. An average firm operates in 4.5 counties and covers 3 states, with a market value of $40.23 million. To account for the potential impact of significant firm events such as earnings announcements, which could overlap with the dirty energy incident window, we also use the firm-day dummy variable EA to flag if day t is within the [-20, 20] trading-

day window of firm i' earnings announcement. The energy and climate opinion measures in this firm-incident-trading-day sample present a distribution similar to that reported in Table 2. Regarding the county-level variables, an average retail investor representative county in this 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.

3 Retail Trading with Energy and Climate Opinions

This section presents evidence of a link between retail investors' energy and climate opinions and their response to dirty energy incidents.

3.1 Empirical Setup

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

$$Net\ Retail\ Demand_{i,d,t} = \beta_1 Incident_{i,d,t} \times Opinion_{i,y} + \beta_2 Incident_{i,d,t} + \beta_3 EA_{i,t} + \alpha_{i,d} + \gamma Control_{i,t} + \epsilon_{i,d,t}. \tag{2}$$

The outcome variable of interest is the buy-sell imbalance in retail trading volume on day t for the pair of firm i and incident with the incident date of d. $Incident_{i,d,t}$ is an indicator equal to one if the date t is within one week (five trading days) of the firm-incident of dirty energy incidents. Following the definition in Eq. (1), $Opinion_{i,y}$ is the energy or climate opinion of firm i's retail investors in the event year y, measured in $Energy$, $Belief$, or $Concern$. Alternatively, we 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-renewable-energy or 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.[15] Plus, we include the Firm-IncidentDate fixed effect ($\alpha_{i,d}$) to absorb any variations constant for each Firm-IncidentDate 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 i and by IncidentDate d.

One concern is that our measure of energy or climate opinions may also capture the views of other stakeholders (e.g., officers, directors, employees) who reside in firms' major locations. Following a negative energy incident, firms with pro-renewable-energy or 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, as 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, as presented in Appendix Table IA.2, we do not find evidence that energy or climate opinions are informative for the disclosure of future dirty energy incidents at either the firm or county level, which mitigates concerns about reverse causality driving our results. Lastly, our measure of energy or climate opinions could also be related to stricter local policies or regulations toward dirty energy activities, which may contribute to the decline in retail investor demand. We conduct detailed tests to address this concern in Section 4.2.

[15]The results are robust when we exclude dirty energy incidents that occur on the same day of a firm's earnings announcement in Appendix Table IA.1.

3.2 Main Results

As prerequisites, column (1) of Table 4 reports the test result without considering investor opinions. The coefficient for $Incident$ does not show statistical significance, implying that, without accounting for heterogeneity among investors such as differences in views about renewable energy or global warming, retail investors on average do not react to dirty energy incidents. This finding is consistent with previous literature that finds no evidence suggesting ESG disclosures influence an average retail investor (Moss, Naughton, and Wang, 2024).

[Table 4 here]

Columns (2) to (10) present the baseline specifications following Eq. (2), with $Opinion$, or its alternatives of $Opinion(Major)$ and $Opinion(HQ)$, measured by $Energy$ in columns (2) to (4), by $Belief$ in columns (5) to (7), and by $Concern$ in columns (8) to (10). The key coefficient β_1 is negative and statistically significant throughout the columns, indicating that pro-renewable-energy and pro-climate-change opinions negatively affect retail investors' net buying of stock shares right after the firm suffers a negative energy activity related incident. Results remain consistent when we use alternative opinion measures $Opinion(Major)$ or $Opinion(HQ)$.

To gauge the economic significance of this negative effect, we use the average opinion score in a back-of-the-envelope calculation. For instance, in column (2), the coefficient on $Incident \times Opinion$ is -0.099. Given the average $Energy$ score of 66.09, this implies an average reduction in retail net demand of $-0.099\% \times 66.09 = -6.54\%$ driven by retail investors' pro-renewable energy opinion following a dirty energy incident. Based on an average daily trading volume of 755,203 shares, this reduction corresponds to a decrease of approximately 49,390 shares in retail trading volume. Similarly, based on the estimates in columns (5) and (8), the reductions in retail net demand associated with $Belief$ and $Concern$ about global warming are 3.582% and 2.711%, respectively, following a dirty energy incident.

It is worth noting that our findings are unlikely to be driven by major firm-level events such as earnings announcements, as we explicitly control for EA following Eq. (2). The β_3 estimates for EA also serve as useful benchmarks for interpreting the economic magnitude of the β_1 estimates discussed above. The effects of $Energy$, $Belief$, and $Concern$ are notably large relative to the

average increase in retail net demand of 0.69% to 0.80%, as implied by the β_3 estimates, during the [-20, +20] trading-day window surrounding earnings announcements.

A further comparison between the estimates of β_1 and β_2 in Eq. (2) provides insights into the threshold levels of energy and climate opinion scores that trigger a negative retail investor response to dirty energy incidents. For instance, in column (2), where β_1 is -0.099 and β_2 is 6.615, the implied threshold score for the energy score is approximately 66.8 (i.e., 6.615/0.099). Similarly, columns (5) and (8) yield a threshold of 74 for climate belief and 66.6 for climate concern, respectively. These results suggest that a firm with a negative energy-related incident is likely to experience net retail selling if more than 66.8% of its retail investors are supportive of renewable energy, or if 74% or 66.6% believe in or are concerned about global warming, respectively. Mapping these thresholds onto the YCOM data, we find that among U.S. mainland counties with Compustat firm footprints, only 25.9% (based on $Energy$), 33.1% (based on $Belief$), and 23.9% (based on $Concern$) exceeded their respective thresholds in 2014. By 2023, these figures rose to 78.2%, 74.9%, and 50.3%, respectively, highlighting the growing investment implications of the substantial rise in support for renewable energy and recognition of global warming over the past decade.

3.3 Detailed Survey Questions in YCOM

Besides the three key questions used in the main tests, YCOM also includes a rich set of detailed survey questions covering four dimensions: beliefs, risk perceptions, policy support, and behaviors, which emphasize different aspects of global warming and aim to gauge public understanding of its causes and consequences. These data provide rich dimensions for examining the specific views that may affect investor behavior. Following the approach in Eq. (1), we construct detailed firm-level retail investor opinion measures based on these additional YCOM questions. We then repeat the tests from Table 4 and report the statistically significant results in Figure 4, which include eight detailed questions:

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

[Figure 4 here]

For each of the eight detailed questions, Figure 4 summarizes the estimates of β_1 from Eq. (2) and marks the threshold value of β_2/β_1 with red triangles.[16] Similar to *Energy*, *Belief*, and *Concern* in our main tests, these views also exert a statistically significant negative effect on retail trading following dirty energy incidents. Taking *FutureGen* as an example, with an estimated β_1 of -0.055, an average opinion score of 71.67 would imply a decline in net retail demand of 3.94% following a dirty energy incident, and the firm is likely to experience net retail selling if more than 72.71% of its retail investors believe that "global warming will harm future generations of people."

Notably, among the eight questions, some are closer to egoistic concerns (e.g., *Personal*), others are closer to altruistic or pro-social preferences (e.g., *FutureGen*, *HarmDev*). Taken together, these tests indicate that the effect of energy and climate opinions on retail investors is correlated with a combination of self-regarding and other-regarding motivations.

4 Energy and Climate Opinion versus Other Factors

A potential confounding issue in our setup is the presence of omitted variables that may influence these opinion measures. Firstly, these variables could be associated with the risk aversion of retail investors, 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 dirty energy incidents. Secondly, the dirty energy incidents we focus on also carry significant environmental and social consequences (see the descriptions in Appendix 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 energy and climate. Third, energy

[16] The detailed regression results and summary statistics for the eight opinion measures are reported in Appendix Table IA.3.

and climate opinions may reflect local political polarization, which also influences energy-related policies and regulations. In that case, policy stringency—rather than investor opinions—could be driving our results. We construct a set of tests in this section to address these concerns.

4.1 General Risk Aversion and Other Risky Incidents

We first contrast our results on dirty energy incidents with the remaining RepRisk environmental and social (ES) incidents which are not directly linked to energy activities. As shown in Appendix Figure IA.4, the largest proportion, approximately 23%, of these incident firms operate in the "wholesale, retail, and some services" sector, with the remainder more broadly distributed across the other nine industry categories; the energy and utilities sectors account for only a very small share. This industry distribution differs substantially from that of dirty energy incident firms reported in Figure 1.

Applying the nearest-neighbor propensity score matching approach (Rosenbaum and Rubin, 1983; Shipman, Swanquist, and Whited, 2017), we match each dirty energy incident in the main test sample to other ES incidents reported in RepRisk during the same sample period using a one-to-one matching procedure without replacement. The propensity scores are estimated via a logistic regression model based on the incident severity score and firm characteristics, including total assets, book-to-market ratio, and leverage. Together, there are 5,404 firm-incident observations of other ES incidents by 548 unique firms.[17] Consistent with the main analysis, we then apply a [-20, +20] trading-day window around each matched incident and construct a corresponding Firm-IncidentDate-Day sample. Appendix Tables IA.6 reports the summary statistics for this sample, in which key test variables such as *Net Retail Demand*, energy and climate opinion measures are similar to those in our main test sample reported in Table 3.

Using this extended firm-incident-date sample that incorporates a broader range of ES incidents from RepRisk, we construct three incident indicators: *Incident* follows the same definition in section 3.1 to mark dirty energy 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

[17] See Appendix Tables IA.4 and IA.5 for incident summaries and firm characteristics of other ES incidents in the propensity-score–matched sample.

social risk (S) incidents which exclude these dirty energy incidents. If the negative effect on retail trading captured by our specifications truly reflects the impact of energy and climate opinions, the occurrence of risk incidents that are less or even not directly linked to energy activities 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 whether energy and climate opinions have a comparable effect on retail investors' reactions when faced with negative ES events that are not directly linked to dirty energy. The results are reported in Table 5.

[Table 5 here]

The full sample tests in columns (2) to (4) show negative and significant coefficients of $Incident \times Opinion$, close to the main findings in Table 4. In contrast, the coefficient of $Incident^{Other\ E} \times Opinion$ is much smaller and statistically weaker, and the coefficient of $Incident^{Other\ S} \times Opinion$ is insignificant. These results highlight the nuanced role of energy and climate opinions: such views significantly influence retail investors' reactions to risk incidents related to dirty energy issues, they have a very 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 renewable energy and global warming.

It is also noteworthy that in column (1), the coefficient estimate on $Incident^{Other\ E}$ is negative and statistically significant, suggesting the difference of *Other E* incidents with dirty energy incidents that the average retail investor's response to those non-energy-related negative environmental news is not conditional on energy and climate opinions. Furthermore, in columns (6) to (12), we also examine other ES incidents alone in a parallel test to Eq. (2). The results consistently suggest that retail investors' pro-energy and pro-climate opinions do not affect retail trading following such events to the same extent as they do in response to dirty energy incidents.

Sustainable finance is mixed with motivations about *value* and *values* (Starks, 2023). If general risk aversion operates as an omitted variable, another potential explanation for our results, is that the effect of energy and climate opinions following dirty energy incidents simply reflects the perceived risk of these incidents to firms' financial value. In addition, dirty energy incidents may coincide with other risky events that have significant negative financial implications. Table 6 tests

this conjecture by including firm stock returns in the main specification.

[Table 6 here]

Across columns in Table 6, retail net demand is consistently positively related to lagged stock returns and negatively related to contemporaneous stock returns, consistent with stock returns being one of the most accessible financially material signals for retail investors. However, the negative effects of $Opinion \times Incident$ on retail net demand remain robust after controlling for stock returns, suggesting that general risk aversion to negative financial implications is not the main force driving our findings.

Taken together, the above comparisons of using firm-level signals that are risky but unrelated to energy activities, either in the form of other RepRisk incidents or firm stock returns as financial signals, help alleviate concerns that our estimates simply capture reactions to extreme tail-risk events or general ES-related catastrophes.

4.2 Local Politicization and Policy Stringency

One potential explanation for our results is that they may simply reflect the effects of local political polarization, which not only relates to investor opinions but also influences policies and regulations. For instance, firms experiencing dirty energy incidents in areas with pro-renewable-energy or pro-climate views may also face higher regulatory risk towards energy activities, which could contribute to the observed decline in retail investor demand.

We test this conjecture using local political polarization data from the MIT Election Data and Science Lab. Following section 2.2 to focus on firms' retail investors representative counties like headquarters and major operating locations, we use county-level outcomes from the most recent presidential election at the time of each dirty energy incident to construct four firm-incident-level measures of local political orientation. $Blue_{i,e}$ is a continuous variable representing the percentage of blue (Democratic-leaning) counties among these retail representative locations. In our test sample, $Blue$ is correlated at 0.61 with $Energy$ and around 0.58 with both $Belief$ and $Concern$, indicating a moderate association between these opinion measures and local political leanings. We also construct three indicator variables: $I(Blue)_{i,e}$ to flag if at least one county is blue, $I(All\ Blue)_{i,e}$

to flag if all counties are blue, and $I(Blue\&Red)_{i,e}$ to flag if a firm's retail representative locations include both blue and red counties.

[Table 7 here]

Table 7 presents the results of our main test after controlling local politicization. In all specifications, the magnitude of the key coefficient estimates on $Incident \times Energy$, $Incident \times Belief$, or $Incident \times Concern$ remains negative and statistically significant, with magnitudes comparable to those reported in Section 3.2. This suggests that local political leanings do not materially influence our main results in any of the saturated models. These findings help alleviate concerns that our estimates are primarily driven by political polarization or differences in local energy and climate policy stringency.

4.3 Energy or Climate Opinions, Demographics, and IV estimation

General risk aversion and demographics are naturally intertwined as the latter could shape people's tolerance for risk. Meanwhile, the original YCOM data are also closely linked to local demographics. Thus, it is not surprising that, as reported in Appendix Table IA.7, local energy and climate opinions are related to county characteristics. These opinions are higher in counties with larger populations, higher education, and older residents, and lower in counties with a higher share of White populations; support for renewable energy decreases with housing values, whereas concern about climate change increases. In contrast, all opinion measures appear to be only weakly related to housing returns or income per capita.

Therefore, if general risk aversion operates as an omitted variable, we need to consider the possibility that retail investors' demographics may affect our findings. Although in our main test in Eq. (2) the Firm–IncidentDate fixed effect $\alpha_{i,d}$ already absorbs demographic characteristics of a firm's retail investor base, provided these characteristics remain invariant during the incident window, because we identify the effect of energy and climate opinions through their interaction with *Incident*, it is still possible that omitted variables could influence our estimates through similar

interaction terms. We address this concern by including these demographic interaction terms in our main specification. Following Section 2.4, we construct the corresponding firm-level demographic measures using firms' major locations and headquarters. The results are reported in Table 8.

[Table 8 here]

In column (1), without considering energy and climate opinions, retail trading after dirty energy incidents is only affected by income. In contrast, columns (2) to (4) show that the effects of the opinion measures in our main findings remain robust even after including all interaction terms with the demographic variables discussed above.

We then follow Lin (2020) and use education as an IV for energy and climate opinions. Education is strongly related to *YCOM Opinion* and could plausibly affect stock market participation (*Div ratio*), the two components used to construct *Opinion* in Eq. (1). At the same time, there is no clear a priori reason how education would directly affect retail investors' net buying following dirty energy incidents. Thus, education is likely to be correlated with retail responses to dirty energy incidents through its impact on energy and climate opinions. In columns (5) to (7), using education as a valid instrument, the interaction with *Incident* remains negative and significant, even after including other demographic measures of retail investors. These results further alleviate concerns that our main findings are driven by omitted variables, such as general risk aversion correlated with retail investors' other characteristics.

5 Heterogeneity in Retail Opinions' Influence

Next, we study the potential role of heterogeneity in how energy and climate opinions influence retail investors' trading behavior. This analysis explores variation across different firms and incident types.

5.1 Incident Properties

If pro–clean-energy retail investors react negatively to dirty energy incidents, their responses should be strongest for incidents with the most severe consequences. Incident severity could therefore be

an important trigger of investor reactions. To test this conjecture, we classify dirty energy incidents using three measures that capture the magnitude of their impacts.

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. Besides the incident records, RepRisk also constructs a risk index (the RepRisk Index RRI) 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. Following Houston, Lin, Shan, and Shen (2022), the other two measures are derived from changes in a firm's RepRisk Index (RRI). 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 $Incident \times Opinion$ ($Energy$, $Belief$, or $Concern$) 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 energy and climate 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 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.8 and IA.9, 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.

5.2 Local Bias

As explained in Section 2.2, we establish the linkage between local energy and climate 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 10 here]

In Table 10, 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 (12), our main coefficient on $Incident \times Opinion$ ($Energy$, $Belief$, or $Concern$) remains statistically and economically very similar to our main specification. In columns (1) to (3), we find that the estimated coefficient on the triple interaction $Incident \times Opinion \times Ln(MV)$ is positive and statistically significant, which means the effect of energy and climate opinions on incident firms is getting weaker as firms grow bigger. Similarly, columns (4) to (9) show that the effect also weakens as the number of operating counties or states increases.

In column (11), 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 investor opinions is more applicable to local firms whose operations are clustered within a specific region. Similarly, Column (10) or (8), which uses $Energy$ or $Concen$, yields comparable results, though the statistical significance is somewhat weaker.

6 Alternative Measures for Retail Trading Using Robinhood

In this section, we use Robinhood user holding records from Robintrack as an alternative retail 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, Naughton, and Wang (2024), $RH_{i,t}$ measures the activities of Robinhood users of firm i on day t, either in $\Delta RI_{i,t-1,t+1}$, the change of the number of users from day $t-1$ to $t+1$ scaled by firm total asset, or in $\Delta RI\ volatility_{t-1,t+1}$, the hourly volatility of the number of users from day $t-1$ to $t+1$ scaled by firm total asset.[18] The first one is a proxy of the growth of the retail

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

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 (5) of Table 11, the occurrence of dirty energy incidents does not affect user growth or user activeness on the Robinhood platform. Columns (2)–(4) and (6)–(8) show that energy and climate opinions negatively affect user growth, ΔRI, and user activeness, $\Delta RI_{volatility}$, in the presence of a dirty energy incident.

Because Robinhood data do not provide detailed user-level trading information, these results do not directly speak to net selling versus net buying. Nevertheless, they are consistent with our earlier findings based on TAQ data. The negative coefficients on $Incident \times Energy$, $Incident \times Belief$, and $Incident \times Concern$ in the Robinhood sample imply a deterioration in retail investor activity. Echoing the main results, these findings provide additional evidence that energy and climate opinions shape retail trading decisions when dealing with dirty energy activities.

7 Conclusion

Energy finance is motivated in part by views on clean energy and climate change. Understanding the drivers of this investment demand is thus crucial to assessing the ability of finance to facilitate a range of energy transition objectives. In this paper, we explore these drivers by combining ten years of county-level survey records with the archival data of retail trading. We provide novel evidence that dirty energy incidents affect retail investors only when they are supportive of renewable energy, 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, Stambaugh, and Taylor, 2021).

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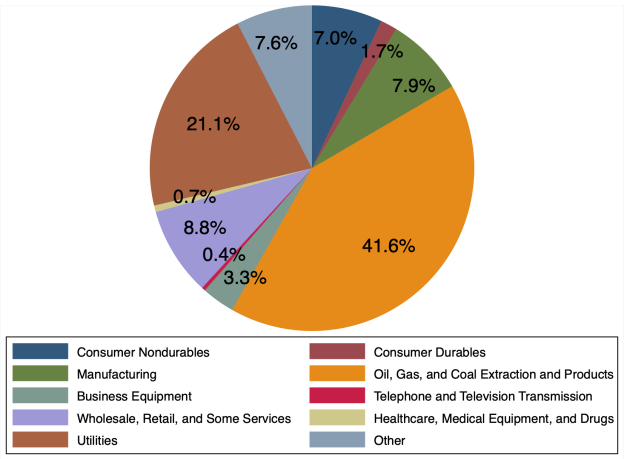
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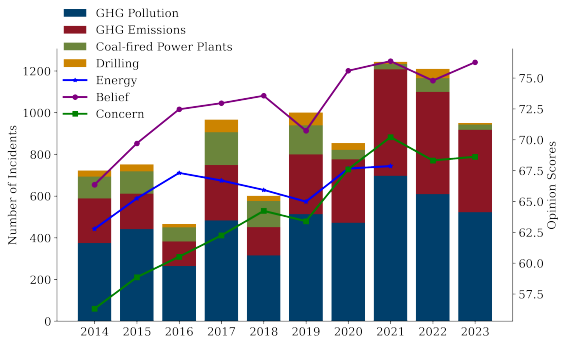
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Figures



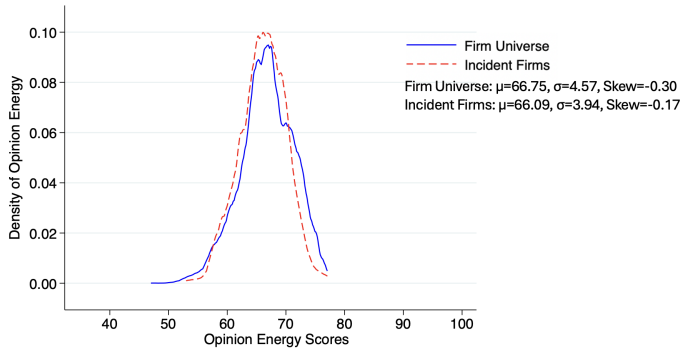
(a) Industry Distribution



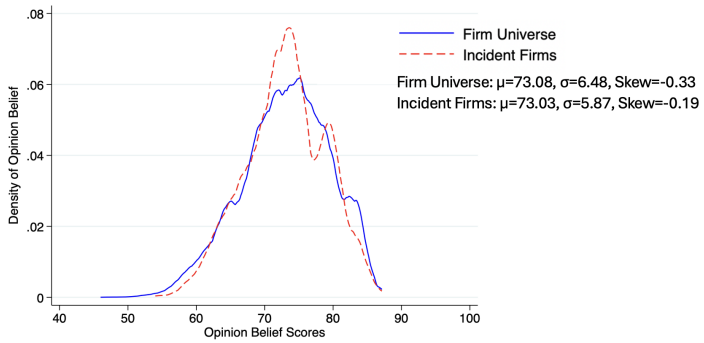
(b) Dirty Energy Incidents and Related Opinions

Figure 1: Dirty Energy Incidents
Panel (a) shows the industry distribution of dirty energy incident firms in our sample, following the Fama-French 10 industry classification. In Panel (b), the bar chart presents the average number of the four types of climate incidents as defined in the Appendix A.2; the line chart plots the average energy and climate change opinions (*Energy*, *Belief*, and *Concern*) in the firm-incident sample.

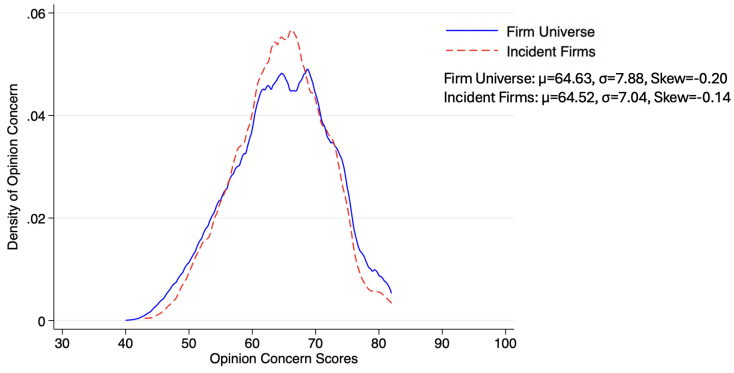
Figure 2: Opinion Score Distribution
In Panel (a), the figure plots the distribution of *Energy* opinion scores during 2014 to 2021 in our dirty incident firm sample as the dashed red line and in the sample of the firm universe as the solid blue line. Figures in Panels (b) and (c) are similar ones for *Belief* and *Concern* opinion scores, respectively, during 2014 to 2023. The firm universe includes all firms that have historical headquarter information in SEC 8-k filing.



(a) Opinion Energy

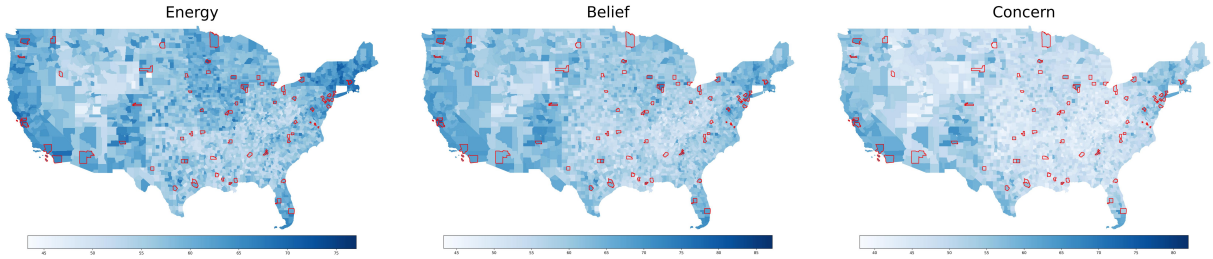


(b) Opinion Belief

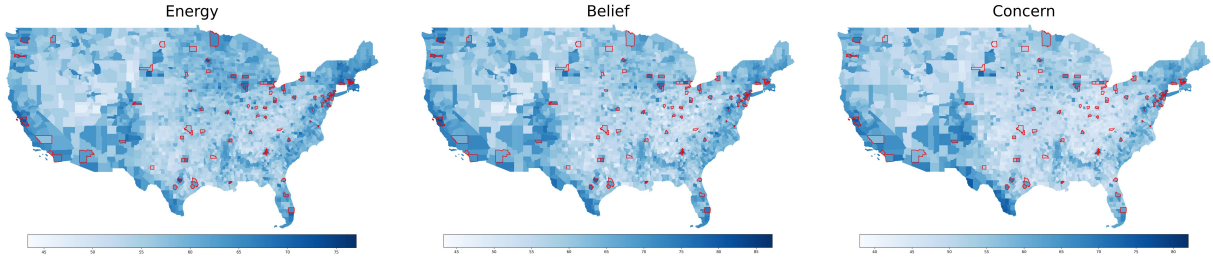


(c) Opinion Concern

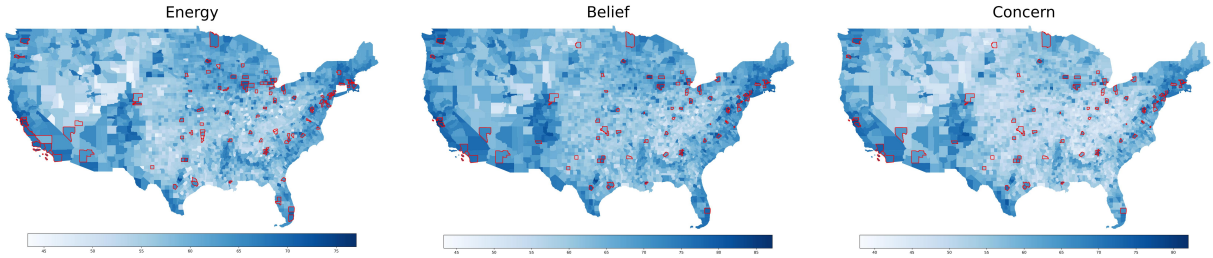
Figure 3: Snapshots of Yale Climate Change Survey Scores
This figure maps the county-level YCOM opinion scores, *Energy* (2014, 2019, 2021), *Belief* and *Concern* (2014, 2019, 2023). Counties where firms with dirty energy incidents are headquartered or operate are highlighted in red.



(a) Energy and Climate Opinions in 2014



(b) Energy and Climate Opinions in 2019



(c) Energy Opinion in 2021 and Climate Opinions in 2023

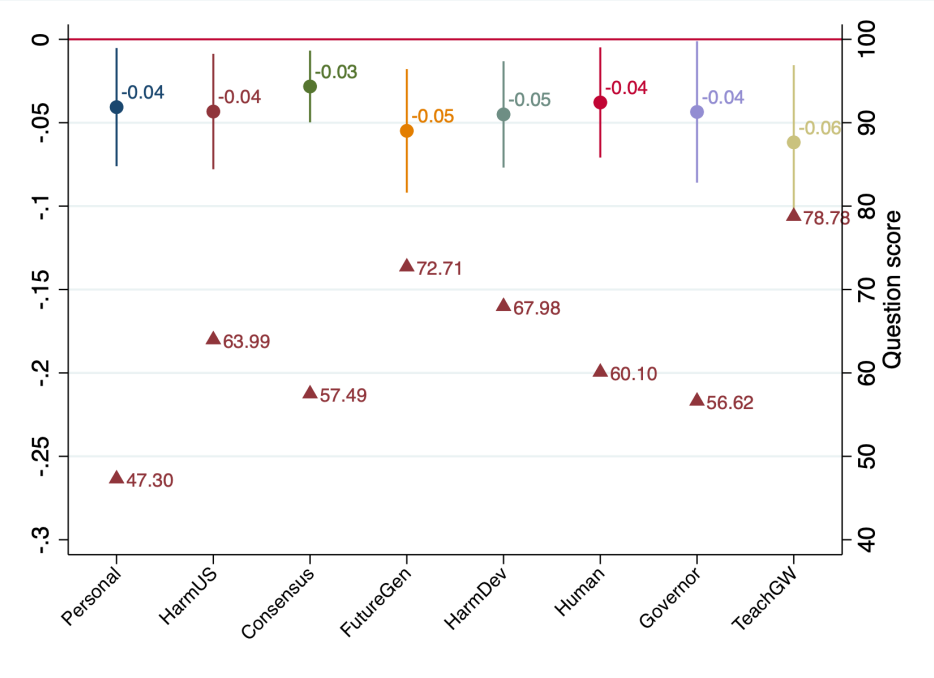


Figure 4: Results on Alternative Detailed Survey Questions in YCOM
Following a similar test of Eq. (2), this chart summarizes the estimates of the coefficient β_1 on *Incident* $\times$ *Alt Opinion* with the 90% confidence intervals in Table IA.3. The numbers with red triangles represent the value β_2/β_1. The eight detailed survey questions are explained in Appendix A.1.

Tables

Table 1: Distribution of Dirty Energy Incidents
This table reports the distribution of dirty energy incidents in the main sample from 2014 to 2023. Panel A shows the distribution across four incident categories and Panel B lists the distributions of incident severity-, reach- and novelty-scores defined by RepRisk.

Panel A: Summaries of Dirty Energy Incidents					
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 Incident 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 Retail Energy and Climate Opinion Measures
This table reports the summary statistics of energy opinion measures from 2014 to 2021 and climate opinion measures from 2014 to 2023. The observations are at the firm-indicent pair level for dirty energy incidents. Panel A includes three sets of variables for *Energy*, *Belief*, and *Concern*, following the definition in Eq. (1). Panel B provides the correlation matrix among these variables. All variables are defined in Appendix A.1.

Panel A: Energy and Climate Opinion Scores

	count	mean	sd	min	p25	p50	p75	max
Opinion Energy	3627	66.09	3.94	53.00	63.36	66.30	69.00	77.05
Opinion Energy(Major)	3627	65.27	3.40	54.14	63.21	65.50	67.60	76.09
Opinion Energy(HQ)	3627	66.72	4.22	53.00	64.00	67.32	69.69	77.05
Opinion Belief	4686	73.10	5.92	54.00	69.39	73.26	77.40	87.15
Opinion Belief(Major)	4686	71.61	5.18	56.49	68.27	72.07	75.44	87.15
Opinion Belief(HQ)	4686	73.83	6.09	54.00	70.19	74.76	78.52	87.15
Opinion Concern	4686	64.55	7.09	43.00	59.93	65.02	69.46	81.99
Opinion Concern(Major)	4686	63.30	6.36	44.36	59.01	63.53	67.42	81.99
Opinion Concern(HQ)	4686	65.11	7.28	43.00	60.34	65.19	70.44	81.99

Panel B: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Opinion Energy	1								
Opinion Energy(Major)	0.700***	1							
Opinion Energy(HQ)	0.919***	0.662***	1						
Opinion Belief	0.902***	0.693***	0.845***	1					
Opinion Belief(Major)	0.655***	0.932***	0.626***	0.754***	1				
Opinion Belief(HQ)	0.831***	0.666***	0.906***	0.937***	0.729***	1			
Opinion Concern	0.832***	0.638***	0.790***	0.934***	0.726***	0.883***	1		
Opinion Concern(Major)	0.592***	0.837***	0.574***	0.727***	0.936***	0.708***	0.796***	1	
Opinion Concern(HQ)	0.773***	0.604***	0.841***	0.878***	0.698***	0.934***	0.950***	0.769***	1

Table 3: Summary statistics of the Firm-IncidentDate-Day Sample for Dirty Energy Incidents

This table reports the summary statistics of our main sample at the Firm-IncidentDate-Day level from 2014 to 2023. All variables are defined in Appendix A.1.

	count	mean	sd	min	p25	p50	p75	max
Net Retail Demand (%)	191643	-1.68	17.30	-100.00	-9.98	-1.07	6.92	100.00
MV (in million)	191643	129.14	245.91	0.01	12.97	45.10	192.26	2852.31
HHI^{map}	191643	0.25	0.21	0.03	0.09	0.19	0.31	1.00
Num_county	191643	4.50	1.44	0.00	3.64	4.80	5.49	7.88
Num_state	191643	3.00	0.96	0.00	2.56	3.37	3.76	3.97
Opinion Energy	148341	66.09	3.94	53.00	63.36	66.30	69.00	77.05
Opinion Belief	191643	73.10	5.92	54.00	69.39	73.26	77.40	87.15
Opinion Concern	191643	64.55	7.09	43.00	59.93	65.01	69.46	81.99
EA	191643	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Education	191643	33.82	9.26	12.70	27.70	30.56	39.10	70.10
Population	191643	2.05	1.63	0.00	0.79	1.48	3.51	10.09
Income	191643	70.08	25.59	0.00	53.83	63.02	75.89	193.62
White	191643	0.52	0.17	0.16	0.34	0.49	0.64	0.96
Age	191643	35.33	3.13	27.50	32.50	35.28	37.50	52.50
HouseValue	191643	200.82	59.70	0.00	157.94	194.98	236.60	451.56
HouseReturn	191643	0.07	0.05	-0.31	0.04	0.06	0.09	0.26

Table 4: Retail Trading with Energy and Climate Opinions

This table presents results from regressions of net retail demand (in percentage) on the interaction of local energy and climate opinions with the occurrence of a dirty energy incident. The sample covers firm-incident pairs of dirty energy incidents from 2014 to 2023, and observations are at the Firm-IncidentDate-Day level on days -20 to +20 around each firm incident pair. Standard errors two-way clustered by Firm and IncidentDate 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)	(10)
		Energy			Belief			Concern		
Incident	0.057	6.615***	6.625**	4.654**	3.625**	2.752*	3.004**	2.799**	2.555*	2.205*
	(0.105)	(2.361)	(2.582)	(2.134)	(1.545)	(1.663)	(1.506)	(1.281)	(1.303)	(1.224)
Incident × *Opinion*		-0.099***			-0.049**			-0.042**		
		(0.035)			(0.021)			(0.019)		
Incident × *Opinion*(*Major*)			-0.101***			-0.038*			-0.039**	
			(0.039)			(0.023)			(0.020)	
Incident × *Opinion*(*HQ*)				-0.069**			-0.040**			-0.033*
				(0.031)			(0.020)			(0.018)
EA	0.803***	0.692***	0.691***	0.691***	0.802***	0.802***	0.801***	0.801***	0.802***	0.801***
	(0.183)	(0.180)	(0.180)	(0.180)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)
N	191643	148341	148341	148341	191643	191643	191643	191643	191643	191643
R^2	0.111	0.118	0.118	0.118	0.111	0.111	0.111	0.111	0.111	0.111
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days									

Table 5: Robustness: Dirty Energy Incidents versus Other ES Incidents

This table presents results from regressions of net retail demand (in percentage) on the interaction of local energy and climate opinions with the occurrence of dirty energy incidents, other E incidents, and other S incidents. Other E and S incidents are matched with dirty energy incidents by incident severity and firm characteristics. Columns (1) to (4) include all three types of incidents. Columns (5) to (8) report results in only other environmental incidents. Columns (9) to (12) report results in only other social incidents. These three samples' observations are at the Firm-IncidentDate-Day level on days -20 to +20 around each firm incident pair. Standard errors double-clustered by Firm and IncidentDate 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)	(10)	(11)	(12)
		Energy	Belief	Concern		Energy	Belief	Concern		Energy	Belief	Concern
Incident	0.125	6.302***	3.266**	2.346*								
	(0.112)	(2.289)	(1.537)	(1.247)								
Incident × *Opinion*		-0.094***	-0.043**	-0.034*								
		(0.034)	(0.020)	(0.019)								
$Incident^{\text{Other E}}$	-0.217*	3.458*	1.723	0.641	-0.182	3.520*	1.754	0.671				
	(0.124)	(2.082)	(1.477)	(1.132)	(0.125)	(2.083)	(1.481)	(1.134)				
$Incident^{\text{Other E}} \times Opinion$		-0.055*	-0.027	-0.013		-0.055*	-0.027	-0.013				
		(0.032)	(0.020)	(0.018)		(0.032)	(0.020)	(0.018)				
$Incident^{\text{Other S}}$	0.104	-2.106	-1.401	-0.633					0.146	-2.030	-1.335	-0.579
	(0.136)	(2.766)	(1.573)	(1.235)					(0.137)	(2.767)	(1.571)	(1.234)
$Incident^{\text{Other S}} \times Opinion$		0.034	0.020	0.011						0.034	0.020	0.011
		(0.041)	(0.021)	(0.018)						(0.041)	(0.020)	(0.018)
EA	0.514***	0.432***	0.514***	0.514***	0.265	0.174	0.265	0.265	0.210	0.226	0.211	0.210
	(0.154)	(0.141)	(0.154)	(0.154)	(0.196)	(0.200)	(0.196)	(0.196)	(0.217)	(0.227)	(0.217)	(0.217)
N	410336	327901	410336	410336	108161	90157	108161	108161	96845	77155	96845	96845
R^2	0.109	0.116	0.109	0.109	0.120	0.126	0.120	0.120	0.084	0.089	0.084	0.084
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days											

Table 6: Robustness: Stock Returns

This table presents results from regressions of retail order imbalance (in percentage) on the interaction of local energy and climate opinions with the occurrence of a dirty energy incident, controlling for the firm's stock returns *Ret* on date $t-1$ and t. Standard errors double-clustered by Firm and IncidentDate 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)	(10)	(11)	(12)
		Energy	Belief	Concern		Energy	Belief	Concern		Energy	Belief	Concern
Incident	0.055	6.468***	3.563**	2.750**	0.052	7.000***	3.734**	2.889**	0.051	6.842***	3.669**	2.840**
	(0.106)	(2.383)	(1.555)	(1.288)	(0.104)	(2.331)	(1.536)	(1.273)	(0.105)	(2.349)	(1.542)	(1.277)
Ret_{t-1}	23.770***	22.856***	22.230***	22.223***					22.320***	19.959***	20.400***	20.392***
	(2.455)	(3.500)	(2.837)	(2.837)					(2.456)	(3.495)	(2.808)	(2.808)
Ret_t					-33.300***	-46.357***	-34.295***	-34.304***	-32.296***	-45.054***	-33.158***	-33.167***
					(6.255)	(8.194)	(6.320)	(6.322)	(6.278)	(8.221)	(6.348)	(6.350)
Incident × *Opinion*		-0.097***	-0.048**	-0.042**		-0.105***	-0.050**	-0.044**		-0.103***	-0.050**	-0.043**
		(0.035)	(0.021)	(0.019)		(0.035)	(0.020)	(0.019)		(0.035)	(0.021)	(0.019)
Incident × Ret_{t-1}		5.239	5.627	5.647						6.932	6.936*	6.957*
		(4.642)	(3.850)	(3.850)						(4.601)	(3.867)	(3.867)
Incident × Ret_t						0.605	3.522	3.532		-0.016	2.839	2.849
						(4.710)	(3.878)	(3.874)		(4.784)	(3.935)	(3.932)
EA	0.800***	0.690***	0.799***	0.799***	0.811***	0.694***	0.810***	0.810***	0.808***	0.692***	0.808***	0.807***
	(0.182)	(0.181)	(0.182)	(0.183)	(0.186)	(0.182)	(0.186)	(0.186)	(0.185)	(0.182)	(0.185)	(0.185)
N	191632	148330	191632	191632	191634	148332	191634	191634	191632	148330	191632	191632
R^2	0.112	0.119	0.112	0.112	0.113	0.121	0.113	0.113	0.114	0.122	0.114	0.114
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days											

Table 7: Robustness: Local Politicization

This table presents results from regressions of net retail demand (in percentage) on the interaction of local energy and climate opinions with the occurrence of a dirty energy incident, controlling for the county-level political leanings. We identify county-level outcomes in the latest presidential election when a dirty energy incident occurs and measure the local politicization at the firm level using: *Blue*, the percentage of blue counties among a firm's $RIRC$; $I(Blue)$, a dummy equals one if a firm has at least one blue county among its $RIRC$; $I(All\ Blue)$, a dummy equals one if all counties in a firm's $RIRC$ are blue counties; $I(Blue\&Red)$, a dummy equals one if a firm has both blue and counties among its $RIRC$. Standard errors double clustered by Firm and IncidentDate 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)	(10)	(11)	(12)
$Incident$	0.438	5.963**	3.791**	2.893**	0.336	6.725***	3.783**	2.878**	0.336	4.502*	3.158*	2.468*
	(0.310)	(2.829)	(1.760)	(1.420)	(0.339)	(2.549)	(1.614)	(1.321)	(0.339)	(2.711)	(1.721)	(1.388)
$Incident \times Energy$		-0.087*				-0.102**				-0.065		
		(0.046)				(0.040)				(0.043)		
$Incident \times Belief$			-0.052**				-0.053**				-0.043*	
			(0.026)				(0.023)				(0.025)	
$Incident \times Concern$				-0.045*				-0.046**				-0.038*
				(0.024)				(0.022)				(0.023)
$Incident \times Blue$	-0.457	-0.222	0.095	0.093								
	(0.312)	(0.423)	(0.384)	(0.390)								
$Incident \times I(Blue)$					-0.317	0.056	0.150	0.155				
					(0.330)	(0.394)	(0.369)	(0.378)				
$Incident \times I(All\ blue)$									-0.393	-0.271	0.025	0.039
									(0.334)	(0.411)	(0.386)	(0.391)
$Incident \times I(Blue\ Red)$									0.350	0.655	0.422	0.433
									(0.491)	(0.506)	(0.486)	(0.487)
EA	0.803***	0.692***	0.802***	0.801***	0.803***	0.692***	0.802***	0.801***	0.804***	0.692***	0.802***	0.802***
	(0.183)	(0.181)	(0.183)	(0.183)	(0.183)	(0.180)	(0.183)	(0.183)	(0.183)	(0.181)	(0.183)	(0.183)
N	191643	148341	191643	191643	191643	148341	191643	191643	191643	148341	191643	191643
R^2	0.111	0.118	0.111	0.111	0.111	0.118	0.111	0.111	0.111	0.118	0.111	0.111
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days											

Table 8: Robustness: Retail Investor Demographics

This table presents results from regressions of net retail demand (in percentage) on the interaction of local energy and climate opinions, controlling for interactions of other demographic variables, and IV estimates. The sample is the same as the ones in Table 4. The firm-level retail demographic measures are constructed using firms' major locations and headquarters following Section 2.4: *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; *Income* is the per capita personal income in thousand dollars; $HouseValue$ and $HouseReturn$ measure the local house values and their annual changes; *Population* is the total population of a county in millions. Columns (5) to (7) use *Education*, which is defined as the percent of people who are 25 years or older and have a bachelor's degree or higher in 2010, to instrument for opinion measures of $\hat{Energy}$, $\hat{Belief}$, and $\hat{Concern}$. The first-stage F-statistics are reported at the bottom. Results from the first-stage regression are reported in Appendix Table IA.7. Standard errors double-clustered by Firm and IncidentDate are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Incident	-1.617	3.194	2.550	1.772	4.616	2.986	2.822
	(1.422)	(2.760)	(2.265)	(2.067)	(4.102)	(3.169)	(3.122)
$Incident \times Energy$		-0.074**					
		(0.034)					
$Incident \times Belief$			-0.063**				
			(0.024)				
$Incident \times Concern$				-0.063***			
				(0.024)			
$Incident \times \hat{Energy}$					-0.095*		
					(0.057)		
$Incident \times \hat{Belief}$						-0.069*	
						(0.041)	
$Incident \times \hat{Concern}$							-0.083*
							(0.050)
$Incident \times White$	0.300	-0.181	-0.451	-0.557	-0.340	-0.529	-0.822
	(1.246)	(1.217)	(1.202)	(1.189)	(1.297)	(1.325)	(1.405)
$Incident \times Age$	0.052	0.051	0.056	0.056	0.050	0.057	0.057
	(0.051)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)	(0.049)
$Incident \times Income$	-0.008*	-0.002	-0.001	0.001	0.000	0.000	0.004
	(0.004)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)
$Incident \times HouseValue$	0.002	0.002	0.003	0.004*	0.002	0.003	0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$Incident \times HouseReturn$	-0.854	-0.721	-0.885	-0.524	-0.655	-0.888	-0.422
	(2.055)	(2.055)	(2.036)	(2.012)	(2.066)	(2.035)	(2.039)
$Incident \times Population$	-0.060	-0.091	-0.109	-0.092	-0.099	-0.114	-0.103
	(0.073)	(0.075)	(0.077)	(0.076)	(0.085)	(0.090)	(0.087)
EA	0.801***	0.802***	0.801***	0.801***	0.802***	0.801***	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			
F statistics					18.65	20.44	14.04
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days						

Table 9: Heterogeneity Results on Severity

This table presents results from regressions of net retail demand by volume (in percentage) on the triple interaction of local energy and climate opinions with the occurrence of a dirty energy 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 dirty energy incidents from 2014 to 2023, and observations are at the Firm-IncidentDate-Day level on days -20 to +20 around each firm incident pair. Standard errors double-clustered by Firm and IncidentDate 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)
	I(Severity)			I(Downgrade)			Downgrade		
Incident	5.826**	3.083**	2.282*	-0.211	-1.748	-1.689	0.839	-0.433	-0.863
	(2.324)	(1.480)	(1.243)	(2.900)	(1.926)	(1.547)	(2.276)	(1.529)	(1.245)
Incident × *Severity*	43.805**	26.591**	25.831***	10.035**	8.225***	6.881***	1.405***	1.076***	1.030***
	(20.671)	(11.030)	(7.711)	(3.959)	(2.667)	(2.074)	(0.497)	(0.344)	(0.293)
Incident × *Energy*	-0.088**			0.002			-0.015		
	(0.035)			(0.043)			(0.034)		
Incident × *Energy* × *Severity*	-0.640**			-0.148**			-0.020***		
	(0.315)			(0.059)			(0.008)		
Incident × *Belief*		-0.042**			0.023			0.004	
		(0.020)			(0.026)			(0.020)	
Incident × *Belief* × *Severity*		-0.343**			-0.110***			-0.014***	
		(0.147)			(0.036)			(0.005)	
Incident × *Concern*			-0.035*			0.025			0.011
			(0.019)			(0.023)			(0.019)
Incident × *Concern* × *Severity*			-0.373***			-0.103***			-0.015***
			(0.117)			(0.031)			(0.004)
EA	0.686***	0.798***	0.797***	0.689***	0.799***	0.798***	0.692***	0.802***	0.800***
	(0.181)	(0.183)	(0.184)	(0.180)	(0.183)	(0.183)	(0.180)	(0.183)	(0.183)
N	148341	191643	191643	148341	191643	191643	148341	191643	191643
R^2	0.118	0.111	0.111	0.118	0.111	0.111	0.118	0.111	0.111
Controls	Firm-Event FE, Overlap days, Seasonality (weekdays and months)								

Table 10: Heterogeneity Tests on Home Bias

This table shows results from regressions of net retail demand (in percentage) on the interaction of local energy and climate opinions with the occurrence of a dirty energy 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 dirty energy incidents from 2014 to 2023, and observations are at the Firm-IncidentDate-Day level on days -20 to +20 around each firm incident pair. Standard errors double-clustered by Firm and IncidentDate 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)	(10)	(11)	(12)
	Ln(MV)			Ln(Counties Count)			Ln(States Count)			HHI^{map}		
Incident	87.150***	52.405***	41.951***	16.958**	12.202***	7.954**	17.709*	13.150**	7.857**	1.667	-0.163	1.027
	(29.717)	(17.223)	(15.297)	(7.982)	(4.130)	(3.200)	(9.810)	(5.169)	(3.893)	(4.135)	(2.243)	(1.852)
Incident × *Home Bias*	-4.777***	-2.862***	-2.296***	-2.592	-2.077**	-1.238*	-4.102	-3.409**	-1.809	18.909	14.294*	6.742
	(1.674)	(0.959)	(0.856)	(1.759)	(0.886)	(0.713)	(3.238)	(1.660)	(1.288)	(16.222)	(7.348)	(5.643)
Incident × *Energy*	-1.288***			-0.252**			-0.265*			-0.025		
	(0.445)			(0.122)			(0.150)			(0.062)		
Incident × *Energy* × *Home Bias*	0.071***			0.038			0.061			-0.286		
	(0.025)			(0.027)			(0.049)			(0.249)		
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	0.691***	0.799***	0.799***	0.691***	0.801***	0.801***	0.691***	0.800***	0.800***	0.692***	0.800***	0.800***
	(0.181)	(0.183)	(0.183)	(0.180)	(0.183)	(0.183)	(0.180)	(0.183)	(0.183)	(0.180)	(0.183)	(0.183)
N	148341	191643	191643	148341	191643	191643	148341	191643	191643	148341	191643	191643
R^2	0.118	0.111	0.111	0.118	0.111	0.111	0.118	0.111	0.111	0.118	0.111	0.111
Controls	Firm-Event FE, Overlap days, Seasonality (weekdays and months)											

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. The dependent variable is ΔRI in Columns (1) to (4) and $\Delta RI_{volatility}$ in Columns (5) to (8). 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)	(7)	(8)
	$\Delta RI_{t-1,\ t+1}$				$\Delta RI\ volatility_{t-1,\ t+1}$			
$Incident$	0.004	0.235**	0.201***	0.176**	0.008	0.239***	0.210***	0.180***
	(0.017)	(0.102)	(0.078)	(0.070)	(0.008)	(0.055)	(0.043)	(0.038)
$Incident \times Energy$		-0.003**				-0.003***		
		(0.002)				(0.001)		
$Incident \times Belief$			-0.003**				-0.003***	
			(0.001)				(0.001)	
$Incident \times Concern$				-0.003**				-0.003***
				(0.001)				(0.001)
$Incident^{\text{Other E}}$	-0.008	0.009	0.009	0.009	0.001	0.007	0.007	0.007
	(0.028)	(0.008)	(0.008)	(0.008)	(0.012)	(0.005)	(0.005)	(0.005)
$Incident^{\text{Other S}}$	-0.000	-0.005	-0.005	-0.005	-0.002	-0.002	-0.003	-0.003
	(0.012)	(0.009)	(0.009)	(0.009)	(0.006)	(0.005)	(0.005)	(0.005)
EA	0.006	0.059**	0.059**	0.059**	-0.001	0.028**	0.028**	0.028**
	(0.044)	(0.028)	(0.028)	(0.028)	(0.021)	(0.014)	(0.014)	(0.014)
N	1045241	904203	904203	904203	1116032	965481	965481	965481
R^2	0.013	0.032	0.032	0.032	0.047	0.076	0.076	0.076
Controls	Firm FE and Date FE							

Appendix for
"Are Retail Investors Penalizing Dirty Energy?"

A.1 Variable Definitions

Energy and Climate Opinions	
Opinion - Energy$_{i,y}$	A continuous variable defined as the energy opinion 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 its major establishments and headquarter in year y according to NETS.
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 counties where firm i has its major establishments and headquarter 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 its major establishments and headquarter in year y according to NETS.
Retail Trading	
Net Retail Demand$_{i,e,t}$	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.
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.
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.
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	
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.
$\text{Book/Market}_{i,e}$	A continuous variable measured the book-to-market ratio of a firm i in the quarter before the event e. collected from WRDS Financial Ratios Suite.
$\text{Leverage}_{i,e}$	A continuous variable measured the total debts over total assets of a firm i in the quarter before the event e collected from WRDS Financial Ratios Suite.
$\text{Log(asset)}_{i,e}$	A continuous variable measured the natural logarithm of the total assets of a firm i in the quarter before the event e collected from Compustat.
$Ret_{i,t}$	A continuous variable defined as the stock return of a firm i on date t.
$Ret_{i,t-1}$	A continuous variable defined as the stock return of a firm i on date $t-1$.
$\text{HHI}_{i,e}^{map}$	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.

$\text{NumCounty}_{i,e}$	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.
$\text{NumState}_{i,e}$	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.
$\text{TeachGW}_{i,y}$	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, Naughton, and Wang (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, Naughton, and Wang (2024).

A.2 Climate Change Incidents from RepRisk

Topic Tag	Definition and Issues
Drilling	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.
Coal-fired power plants	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.
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.
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.

A.3 Appendix Figures

Figure IA.1: Climate Change Opinion - Energy
This figure plots the county-level "supportrps" scores in the Yale Climate Change Opinion Survey from 2014 to 2021.

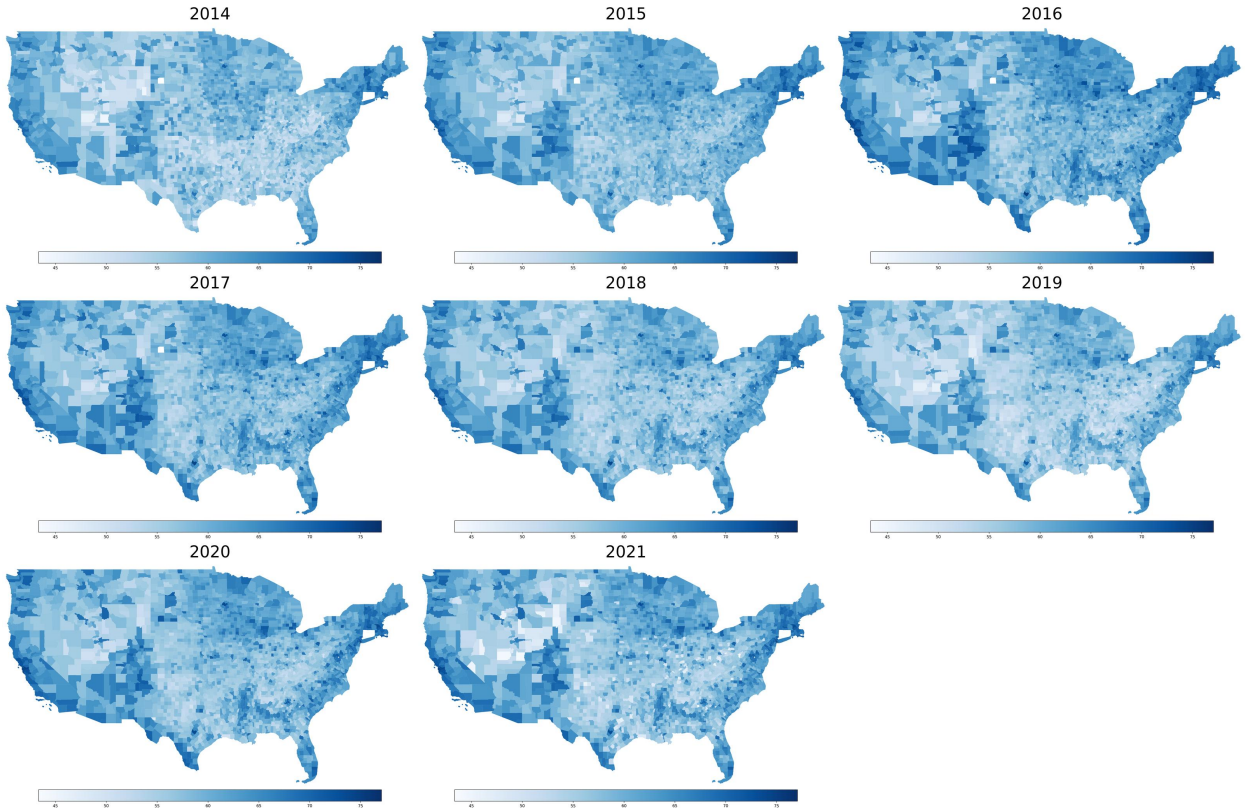


Figure IA.2: Climate Change Opinion - Belief
This figure plots the county-level "happening" scores in the Yale Climate Change Opinion Survey from 2014 to 2023.



Figure IA.3: Climate Change Opinion - Concern
This figure plots the county-level "worried" scores in the Yale Climate Change Opinion Survey from 2014 to 2023.



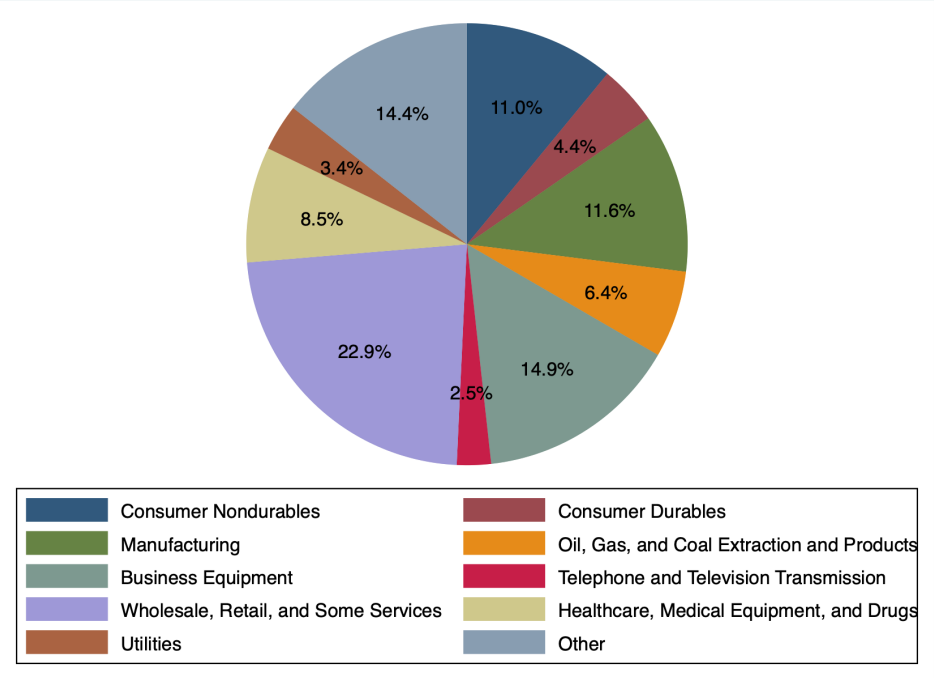


Figure IA.4: Industry Distribution of Other ES Incidents in RepRisk
This figure shows the industry distribution of firms with other environmental (E) or social risk (S) incidents in RepRisk, following the Fama-French 10 industry classification.

A.4 Appendix Tables

Table IA.1: Excluding Dirty Energy Incidents Overlapped with Earnings Announcement
This table presents results from regressions of net retail demand (in percentage) on the interaction of local climate change beliefs with the occurrence of a dirty energy 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 dirty energy incidents from 2014 to 2023, and observations are at the Firm-IncidentDate-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 IncidentDate are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

	(1)	(2)	(3)	(4)
Incident	0.055	6.125**	3.426**	2.769**
	(0.106)	(2.384)	(1.561)	(1.304)
Incident × *Opinion Energy*		-0.092***		
		(0.035)		
Incident × *Opinion Belief*			-0.046**	
			(0.021)	
Incident × *Opinion Concern*				-0.042**
				(0.019)
EA	0.830***	0.719***	0.829***	0.828***
	(0.182)	(0.180)	(0.182)	(0.183)
N	189019	146414	189019	189019
R^2	0.111	0.118	0.111	0.111
Controls	Firm-Event FE, Overlap days			
	Seasonality (weekdays and months)			

Table IA.2: Energy and Climate Opinions and Future Dirty Energy Incidents
This table tests the relationship between energy and climate opinions and the occurrence of dirty energy incidents in the next year. In Panel A for county-level tests, the opinion measures are at the county level and incident occurrence is identified for counties where a firm with at least one dirty energy incident is headquartered. In Panel B for firm-level tests, the opinion measures are constructed at the firm-year level following eq.(1). Standard errors clustered by county in Panel A and by firm and year in Panel B are reported in parentheses. *, ** and *** indicate statistical significance at the ten, five and one percent level, respectively.

Panel A: County-level Tests						
	(1)	(2)	(3)	(4)	(5)	(6)
	$Incident_{y+1}$					
$Energy$	0.040	0.133				
	(0.057)	(0.081)				
$Energy_{y+1}$		-0.024				
		(0.097)				
$Belief$			-0.007	0.052		
			(0.044)	(0.079)		
$Belief_{y+1}$				-0.090		
				(0.082)		
$Concern$					-0.049	-0.016
					(0.039)	(0.071)
$Concern_{y+1}$						-0.048
						(0.075)
N	3008	2632	3384	3384	3384	3384
R^2	0.794	0.893	0.719	0.719	0.719	0.719
Controls	County FE, State×Year FE					

Panel B: Firm-level Tests						
	(1)	(2)	(3)	(4)	(5)	(6)
	$Incident_{y+1}$					
$Energy$	0.007	-0.003				
	(0.009)	(0.015)				
$Energy_{y+1}$		0.019				
		(0.015)				
$Belief$			-0.005	-0.010		
			(0.009)	(0.011)		
$Belief_{y+1}$				0.009		
				(0.009)		
$Concern$					-0.006	-0.010
					(0.007)	(0.009)
$Concern_{y+1}$						0.007
						(0.007)
N	8639	7527	9708	9689	9708	9689
R^2	0.880	0.876	0.883	0.883	0.883	0.883
Controls	Firm FE, Year FE					

Table IA.3: Alternative YCOM Opinion Measures

This table presents results from regressions of net retail demand(in percentage) on multi-dimensional views from YCOM with the occurrence of a dirty energy incident. 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 dirty energy incidents from 2014 to 2023, and observations are at the Firm-IncidentDate-Day level on days -20 to +20 around each Firm-Incident. Standard errors double-clustered by Firm and IncidentDate 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)
	Personal	HarmUS	Consensus	FutureGen	HarmDev	Human	Governor	TeachGW
Incident	1.923*	2.770**	1.625**	3.991**	3.060**	2.275*	2.465	4.865**
	(1.034)	(1.362)	(0.771)	(1.655)	(1.332)	(1.226)	(1.527)	(2.265)
Incident × *Alt Opinion*	-0.041*	-0.043**	-0.028**	-0.055**	-0.045**	-0.038*	-0.044*	-0.062**
	(0.021)	(0.021)	(0.013)	(0.022)	(0.019)	(0.020)	(0.026)	(0.028)
EA	0.801***	0.801***	0.803***	0.802***	0.802***	0.802***	0.998***	0.750***
	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.183)	(0.260)	(0.247)
N	191643	191643	191643	191643	191643	191643	123931	154986
R^2	0.111	0.111	0.111	0.111	0.111	0.111	0.086	0.104
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days							

Panel B: Summary Statistics

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

Table IA.4: Distribution of Other ES Incidents in the Propensity-Score Matched Sample
This table reports the distribution of other ES incidents in the propensity-score matched sample from 2014 to 2023. Panel A shows the distribution across four incident categories and Panel B lists the distributions of incident severity-, reach- and novelty-scores defined by RepRisk.

Panel A: Distribution of Other ES Incidents			
E	S	Count	Percent (%)
0	1	4,395	55.24
1	0	1,141	14.34
1	1	2,420	30.42

Panel B: Distribution of Characteristics			
	Severity (%)	Reach (%)	Novelty (%)
1	66.63	41.59	69.21
2	30.76	37.72	30.79
3	2.61	20.69	–

Table IA.5: Summary Statistics of Firm Characteristics in the Propensity-Score Matched Sample

This table reports summary statistics for firm characteristics in the propensity-score–matched sample of firm–incident pairs from 2014 to 2023. Dirty energy incidents and other ES incidents are reported in Panel A, Panel B, and Panel C, respectively. Firm characteristics are winsorized at 1th and 99th percentiles. All variables are defined in Appendix A.1.

Panel A: Dirty Energy Incidents						
	count	mean	sd	p25	p50	p75
Book/Market	5,019	0.58	0.35	0.31	0.57	0.77
Leverage	5,019	0.30	0.15	0.18	0.30	0.40
Log(asset)	5,019	10.80	1.49	9.83	10.90	12.09

Panel B: Other E Incidents						
	count	mean	sd	p25	p50	p75
Book/Market	3,561	0.56	0.36	0.25	0.54	0.77
Leverage	3,561	0.30	0.15	0.18	0.29	0.43
Log(asset)	3,561	11.00	1.37	10.36	11.15	12.23

Panel C: Other S Incidents						
	count	mean	sd	p25	p50	p75
Book/Market	4,395	0.43	0.36	0.16	0.32	0.63
Leverage	4,395	0.31	0.15	0.20	0.30	0.41
Log(asset)	4,395	10.88	1.53	9.92	11.07	12.32

Table IA.6: Summary Statistics of Key Test Variables in the Propensity-Score Matched Sample

This table reports summary statistics for key test variables at the Firm-IncidentDate-Day level in the propensity-score–matched sample from 2014 to 2023. Other E and S incidents are reported in Panel A and Panel B, respectively. All variables are defined in Appendix A.1.

Panel A: Other E Incidents								
	count	mean	sd	min	p25	p50	p75	max
Net Retail Demand (%)	100168	-1.48	16.68	-100.00	-9.79	-1.04	7.06	100.00
Opinion - Energy	84515	65.96	3.86	51.68	63.50	66.06	68.56	77.05
Opinion - Belief	100168	72.57	5.80	52.40	68.86	72.73	76.54	87.15
Opinion - Concern	100168	63.87	7.12	42.97	59.00	63.84	68.78	81.99
EA	100168	0.36	0.48	0.00	0.00	0.00	1.00	1.00

Panel B: Other S Incidents								
	count	mean	sd	min	p25	p50	p75	max
Net Retail Demand (%)	104808	-1.07	18.00	-100.00	-9.21	-0.45	7.53	100.00
Opinion - Energy	83183	67.12	3.97	51.68	64.64	67.26	69.63	77.05
Opinion - Belief	104808	74.11	6.05	53.21	69.97	74.40	78.84	87.15
Opinion - Concern	104808	66.12	7.30	43.00	61.42	66.57	71.59	81.99
EA	104808	0.35	0.48	0.00	0.00	0.00	1.00	1.00

Table IA.7: Demographic Determinants of Energy and Climate Opinions
This table presents the determinants of opinions using county-year observations from 2014 to 2023, with *Energy*, *Belief*, and *Concern* being reported in Columns (1), (2), and (3), respectively. County-level variables include a list of demographic and economic variables. *Education* is defined as the percent of people who are 25 years or older and 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)	(3)
	Energy	Belief	Concern
Education	0.303***	0.413***	0.366***
	(0.016)	(0.024)	(0.028)
Population	1.176**	0.893**	1.197***
	(0.380)	(0.370)	(0.361)
Income	-0.006	-0.018*	-0.008
	(0.007)	(0.009)	(0.008)
White	-8.746***	-14.938***	-17.979***
	(1.338)	(1.035)	(1.063)
Age	0.142***	0.193***	0.172***
	(0.014)	(0.019)	(0.020)
HouseValue	-0.015***	0.004	0.011***
	(0.003)	(0.003)	(0.003)
HouseReturn	0.597	1.084	-1.952
	(1.636)	(1.616)	(1.442)
N	18810	23449	23449
R^2	0.522	0.628	0.660
Controls		Year FEs	

Table IA.8: Heterogeneity Results on Novel and Severe Incidents
This table presents results from regressions of net retail demand (by volume and in percentage) on the novelty and severity of a dirty energy incident. The novelty of an incident is one if this issue is recurring 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-IncidentDate-Day level on days -20 to +20 around each Firm-Incident. Standard errors double-clustered by Firm and IncidentDate are reported in parentheses. *, **, and *** indicate statistical significance at the ten, fiv,e and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy		Belief		Concern	
$Incident$	5.933*	7.393**	3.107	4.232**	3.051*	4.248**
	(3.101)	(3.407)	(1.979)	(2.128)	(1.791)	(1.791)
$Incident \times Opinion$	-0.088*	-0.108**	-0.041	-0.055*	-0.046*	-0.063**
	(0.046)	(0.051)	(0.026)	(0.028)	(0.027)	(0.027)
$Incident \times I(Novelty = 2)$	1.370		1.168		-0.555	
	(4.507)		(2.619)		(2.168)	
$Incident \times Opinion \times I(Novelty = 2)$	-0.023		-0.017		0.008	
	(0.068)		(0.035)		(0.033)	
$Incident \times I(Novelty = 1 \ \& \ Sev = 2)$		-5.233		-3.655		-3.981
		(6.935)		(4.478)		(3.939)
$Incident \times I(Novelty = 1 \ \& \ Sev = 3)$		19.492		9.022		11.521
		(22.211)		(10.573)		(8.591)
$Incident \times I(Novelty = 2 \ \& \ Sev = 1)$		-2.844		-0.993		-1.663
		(6.108)		(3.638)		(2.702)
$Incident \times I(Novelty = 2 \ \& \ Sev = 2)$		0.121		-0.369		-3.468
		(6.162)		(3.845)		(2.924)
$Incident \times I(Novelty = 2 \ \& \ Sev = 3)$		55.484**		37.919***		31.686***
		(24.334)		(11.559)		(8.252)
$Incident \times Opinion \times I(Novelty = 1 \ \& \ Sev = 2)$		0.071		0.043		0.054
		(0.103)		(0.060)		(0.059)
$Incident \times Opinion \times I(Novelty = 1 \ \& \ Sev = 3)$		-0.281		-0.110		-0.160
		(0.336)		(0.141)		(0.128)
$Incident \times Opinion \times I(Novelty = 2 \ \& \ Sev = 1)$		0.043		0.015		0.027
		(0.091)		(0.048)		(0.040)
$Incident \times Opinion \times I(Novelty = 2 \ \& \ Sev = 2)$		-0.014		-0.003		0.044
		(0.093)		(0.053)		(0.045)
$Incident \times Opinion \times I(Novelty = 2 \ \& \ Sev = 3)$		-0.819**		-0.502***		-0.469***
		(0.374)		(0.157)		(0.129)
EA	0.691***	0.677***	0.801***	0.792***	0.802***	0.792***
	(0.180)	(0.181)	(0.183)	(0.183)	(0.183)	(0.184)
N	148341	148341	191643	191643	191643	191643
R^2	0.118	0.118	0.111	0.111	0.111	0.111
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days					

Table IA.9: Heterogeneity Results on Widespread and Severe Incidents
This table presents results from regressions of net retail demand (by volume and in percentage) on the "reach" and severity of a dirty energy 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-IncidentDate-Day level on days -20 to +20 around each Firm-Incident. Standard errors double-clustered by Firm and IncidentDate are reported in parentheses. *, **, and *** indicate statistical significance at the ten, fiv,e and one percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy		Belief		Concern	
Incident	7.220**	5.315	4.881**	5.653**	3.037*	4.276**
	(3.281)	(3.740)	(2.111)	(2.238)	(1.709)	(1.678)
Incident × *Opinion*	-0.106**	-0.072	-0.064**	-0.070**	-0.044*	-0.058**
	(0.049)	(0.056)	(0.028)	(0.030)	(0.026)	(0.025)
Incident × $I(Reach = 2)$	-3.668		-2.673		-0.214	
	(4.975)		(2.950)		(2.282)	
Incident × $I(Reach = 3)$	8.734		-1.615		-0.389	
	(8.449)		(4.483)		(3.704)	
Incident × *Opinion* × $I(Reach = 2)$	0.050		0.031		-0.003	
	(0.075)		(0.040)		(0.035)	
Incident × *Opinion* × $I(Reach = 3)$	-0.134		0.022		0.006	
	(0.127)		(0.060)		(0.055)	
Incident × $I(Reach = 1$ & $Sev = 2)$		2.889		-1.585		-3.218
		(6.981)		(4.329)		(3.496)
Incident × $I(Reach = 1$ & $Sev = 3)$		52.992**		22.047		37.142**
		(25.442)		(24.656)		(17.378)
Incident × $I(Reach = 2$ & $Sev = 1)$		-1.492		-3.990		-1.236
		(4.846)		(2.978)		(2.195)
Incident × $I(Reach = 2$ & $Sev = 2)$		-6.430		-6.023		-4.784
		(8.428)		(5.438)		(3.755)
Incident × $I(Reach = 2$ & $Sev = 3)$		53.875		30.423**		24.687***
		(35.425)		(11.948)		(7.976)
Incident × $I(Reach = 3$ & $Sev = 1)$		13.098		-2.145		-1.567
		(10.026)		(4.910)		(4.220)
Incident × $I(Reach = 3$ & $Sev = 2)$		4.315		-2.564		-0.822
		(8.358)		(6.337)		(4.582)
Incident × $I(Reach = 3$ & $Sev = 3)$		10.622		11.630		6.130
		(24.414)		(11.524)		(8.011)
Incident × *Opinion* × $I(Reach = 1$ & $Sev = 2)$		-0.057		0.010		0.037
		(0.105)		(0.059)		(0.053)
Incident × *Opinion* × $I(Reach = 1$ & $Sev = 3)$		-0.778**		-0.294		-0.562**
		(0.391)		(0.341)		(0.274)
Incident × *Opinion* × $I(Reach = 2$ & $Sev = 1)$		0.014		0.046		0.009
		(0.073)		(0.040)		(0.033)
Incident × *Opinion* × $I(Reach = 2$ & $Sev = 2)$		0.080		0.067		0.057
		(0.127)		(0.074)		(0.057)
Incident × *Opinion* × $I(Reach = 2$ & $Sev = 3)$		-0.821		-0.407**		-0.370***
		(0.548)		(0.159)		(0.121)
Incident × *Opinion* × $I(Reach = 3$ & $Sev = 1)$		-0.204		0.024		0.019
		(0.151)		(0.065)		(0.062)
Incident × *Opinion* × $I(Reach = 3$ & $Sev = 2)$		-0.081		0.028		0.006
		(0.123)		(0.084)		(0.068)
Incident × *Opinion* × $I(Reach = 3$ & $Sev = 3)$		-0.133		-0.124		-0.057
		(0.365)		(0.151)		(0.111)
EA	0.693***	0.679***	0.802***	0.791***	0.801***	0.791***
	(0.180)	(0.181)	(0.183)	(0.183)	(0.183)	(0.183)
N	148341	148341	191643	191643	191643	191643
R^2	0.118	0.118	0.111	0.111	0.111	0.111
Controls	Firm-Event FE, Seasonality (weekdays and months), Overlap days					