Investor Climate Sentiment and Financial Markets[*,†]

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Abstract

We propose to measure investor climate sentiment by performing sentiment analysis on StockTwits posts on climate change and global warming. In financial markets, stocks of emission (carbon-intensive) firms underperform clean (low-emission) stocks when investor climate sentiment is more positive. We document investors overreaction to climate change risk and reversal in longer horizons. Salient but uninformative climate change events, such as the release of a report on climate change and abnormal weather events, facilitate the investor learning process and correction of the mispricing.

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1 Introduction

Policy-makers are increasingly concerned about the impact of climate risks on economic growth and financial stability. Recent research has documented that stocks of carbon-intensive firms show higher returns than stocks of low-emission firms (Bolton and Kacperczyk, 2021; Hsu et al., 2022). However, sudden shifts in preferences may lead to an increase in sustainable investments as well as disinvestments from emission stocks causing a relative underperformance of the latter (Pástor et al., 2021). In this paper, we provide a behavioural explanation for the shifts in preferences. In particular, we focus on the relationship between investor climate sentiment and the returns of emission (carbon-intensive) and clean (low-emission) stocks.

Climate sentiment measures the investors positive or negative attitudes towards climate change that are not based on the facts at hand (Baker and Wurgler, 2006). When investor climate sentiment is more positive, irrational investors may decrease the relative demand for emission stocks driving prices away from fundamentals. Behavioural finance models predict that investor sentiment can drive prices away from fundamentals (De Long et al., 1990) and because of limits to arbitrage, the mispricing might last for awhile (Pontiff, 1996; Shleifer and Vishny, 1997). Furthermore, because of the lack of salience of the effects of climate change, attention-grabbing events such as the release of a report on climate change, and weather events may lead investors to update their beliefs and correct the mispricing of emission and clean stocks.

Since investor climate sentiment is a latent variable, we propose to perform textual analysis on StockTwits (`https://stocktwits.com/`) posts related to climate change to proxy for investor climate sentiment. StockTwits is the largest social network for investors and traders, the platform is used to share trading ideas and other stock-related information. Similar to Twitter, messages are of a small size and consist of opinions, links, charts and other data. Already in August 2010, Time Magazine inserted StockTwits in the list of Top 50 Websites of 2010. StockTwits has acquired popularity in the last few years, today the platform has a total monthly audience of over 5 million. We use social network data rather than news media data or internet searches because social networks are an increasingly important channel for the dissemination of stock information (Stafford, 2015). Indeed, investors communicate and learn from a combination of news media and social networks, with social influence being a critical factor of the information dissemination process (Hirshleifer and Teoh, 2009; Shive, 2010; Chen and Hwang, 2022). Moreover, given the complexity and the lack of salience of the effects of climate change, social influence is crucial in determining investors sentiment on climate change. Furthermore, since StockTwits has the mission to connect regular traders and investors with each others, it is a less noisy data set to study the effects of climate sentiment on financial markets than other popular social networks such as Twitter that target a general audience (Sun et al., 2016).

Our measure of climate sentiment reflects mainly the views of retail investors rather than institutional investors, among the StockTwits users that report their level of experience, about 24% classify themselves as professionals, 53% as intermediate, 23% as novice.[1] Retail investors are expected to be more subject to behavioural biases and hence more influenced by sentiment than institutional investors which should trade according to fundamental information (Kumar and Lee, 2006). Moreover, there is evidence of retail investors, rather than institutional investors and blockholders, driving the price of carbon-intensive and low-emission stocks when there are salient but uninformative weather events (Choi et al., 2020). We analyse the period from January 2010 to September 2019, and we observe that climate change is generally discussed with a negative tone by climate change sceptics and deniers, while climate change believers tend to use a more positive tone. We find that when social interaction is low, investor climate sentiment tends to be more negative when there are more news on the environmental impact of climate change, and there are more news on the societal debate about this issue. The opposite is observed when social interaction is higher. Furthermore, investor climate sentiment tends to be more positive when there is an increase in the concerns on the business impact of climate change and new research on climate change is released as long as there is social interaction on the matter. As more and more investors share their opinions on climate change, they influence each other views and when news on climate change arise they tend to discuss them with a more positive sentiment. This is consistent with a relative reduction of climate change deniers which are prone to use negative words as compared to climate change believers.

Financial data for the U.S. are retrieved from Refinitiv Eikon Datastream. We use primarily an industry definition to identify emission and clean stocks. Specifically, an emission stock is the stock of a firm that operates in one of the five industry sectors classified as major emission sources by the Intergovernmental Panel on Climate Change (IPCC). The remaining stocks are classified as clean stocks. A long-short portfolio EMC (Emission Minus Clean) is formed by buying a equal- or value-weighted portfolio of emission stocks and selling a equal- or value-weighted portfolio of clean stocks.

[1] We refer to Section A.2 of the Appendix for more details on StockTwits users characteristics.

Importantly, we find that investor climate sentiment is associated with significantly lower EMC returns. Specifically, this result is mainly driven by investors disinvestment from emission stocks. This is in line with Baker and Wurgler (2007) which show that stocks which are hard to value are most affected by sentiment. Given the relative high subjective valuation of firms' environmental performance, emission stocks are expected to be most sensitive to sentiment-based demand. In particular, the relationship between environmental performance and firm value is difficult to assess for several reasons. First, there is a lack of easily available information on firms' environmental performance. Second, such information is hard to process. Third, the effect of a firm's environmental performance on its value depends, among other things, on governments' environmental policies and regulations which are highly uncertain. In two alternative specifications, we use Refinitiv ESG total CO_2 equivalent emissions and emission intensity (total CO_2 equivalent emissions divided by sales or revenues in USD millions) to form the emission and clean portfolios, and we obtain similar results. Furthermore, we document the same reaction to investor climate sentiment of the returns of both energy and non-energy carbon-intensive sectors, confirming that results are not merely driven by oil prices. Moreover, we obtain the same results when we exclude the first year of observations as in 2010 the computation of the sentiment score is based on a smaller number of posts and it shows higher volatility.

We next examine the relationship between investor climate sentiment and long-term returns of the EMC portfolio. We find that the impact of investor climate sentiment on EMC returns decreases as we consider longer horizons and it eventually reverts back to zero. This implies that part of the belief update is irrational as the previous price pattern has reversed.

Furthermore, we study whether salient but uninformative events, such as the release of a report on climate change and abnormal weather events, can help to correct the mispricing induced by irrational investors trading on climate sentiment. Because of limited attention, people are likely to focus on attention-grabbing events which can foster their learning process. We find that EMC returns react positively to investor climate sentiment in months in which there is the release of a report on climate change or temperatures are abnormally warm. Further, the effect of investor climate sentiment on EMC return is still negative but lower in magnitude in months with high perceived climate change risk, an abnormally high number of extreme weather events, abnormally high damages caused by extreme weather events, and high carbon prices. This is consistent with (at least some) investors updating their beliefs and trading to correct the mispricing.

Our results are consistent with the implications of the adaptive markets hypothesis (Lo, 2004), which can help explain the observed time variation in the degree of market efficiency (Neely et al., 2009; Kim et al., 2011; Urquhart and McGroarty, 2016; Le Tran and Leirvik, 2019). We believe that our findings are partly driven by a lack of easily accessible information on firms environmental performance. The subjective valuation of a firm's environmental performance may boost climate sentiment-based demand which together with a higher risk to arbitrage may result in a relative mispricing of emission stocks. Firms should disclose information on their exposure to climate risk to reduce information asymmetries hence improving market efficiency. In the U.S., the Securities and Exchange Commission (SEC) requires firms to self-identify climate related risks that are material to their business in their 10-K report (SEC, 2010). However, the SEC's approach has been criticized for requiring only a qualitative description of climate risks, rather than quantitative metrics (see e.g., Palmiter, 2015; Kölbel et al., 2022). Moreover, despite the disclosure of climate related risks being mandatory, Bolstad et al. (2020) reports that today only 60% of U.S. publicly traded firms reveal some information about climate change. In particular, the largest volumes of information are skewed heavily toward a few carbon-intensive industries and concern valuation risks due to possible transition away from fossil fuels. Furthermore, disclosures around the physical risk of climate change is still very limited. Recently, Hain et al. (2022) have found substantial divergence in firm-level physical risk scores developed by academics and commercial data providers. Hence, financial markets may not adequately account for the physical risk exposure of corporations.

Turning to our main contributions, this paper adds to the literature on the effects of investors beliefs about climate change on stock prices.[2] The extant literature documents that socially responsible firms report lower stock price crash risk (Kim et al., 2014; Wu and Hu, 2019). Similarly, evidence from the option market shows that firms with more carbon-intensive business models (Ilhan et al., 2021) or weaker Environmental, Social and Governance (ESG) practices (Shafer and Szado, 2020) are subject to higher perceived tail risk. Accordingly, Ford et al. (2022) find that in the option market highly rated ESG firms are associated with a more optimistic short-term investor sentiment. Recently, Choi et al. (2020) have found that people revise their beliefs about climate change upwards when experiencing abnormal temperatures. More importantly, clean firms outperform emission firms when concerns about climate change increase unexpectedly (Ardia et al., 2022; Pástor et al., 2022). Furthermore, Antoniuk and Leirvik (2021) find that unexpected

[2]We refer to Venturini (2022) for a detailed revision of the literature on Climate Finance.

political events affect climate-sensitive sectors. Our work differs from the above papers in that we study the link between stock prices and investor climate sentiment, while previous literature has focused mainly on attention on climate change measured either from internet searches (Choi et al., 2020; Ding et al., 2022) or newspaper articles (Engle et al., 2020; Faccini et al., 2021; Ardia et al., 2022; Pástor et al., 2022). Although investor sentiment and attention might be related, they are distinct phenomena. StockTwits data allow us to analyse the investor reaction to information disseminated through traditional outlets such as newspaper articles, without neglecting the effect of social influence on beliefs formation.

This paper also contributes to the behavioural finance literature which shows that investor sentiment can predict market returns over time, and stock returns cross-sectionally (Baker and Wurgler, 2006; Tetlock, 2007; Kaplanski et al., 2015; Kozak et al., 2018; Obaid and Pukthuanthong, 2022). Differently from the extant literature, we focus on investor sentiment about climate change. Another recent work studying sentiment on climate change is Briere and Ramelli (2021). The authors propose a different approach to estimate green sentiment, in particular they use the monthly abnormal flows into environment-friendly ETFs. They observe that changes in green sentiment anticipate a lasting stock outperformance by more environmentally responsible firms, as well as an increase in their capital investments and cash holdings.

Finally, we contribute to the growing literature that uses textual analysis of social networks posts to capture sentiment and disagreement (see e.g. Sun et al., 2016; Renault, 2017; Cookson and Niessner, 2020; Booker et al., 2022; He et al., 2022). Several works have proposed the use of Twitter to measure climate sentiment (Cody et al., 2015; Dahal et al., 2019; Loureiro and Alló, 2020), however there is still limited evidence on the link between climate sentiment and financial markets.

The rest of the article is structured as follows. Section 2 presents the measure of investor climate sentiment. Section 3 describes the data and variables used in the analysis. Section 4 presents the empirical results. Section 5 concludes.

2 Investor Climate Sentiment

To empirically study the relationship between investor climate sentiment and the returns of emission and clean stocks, we need a proxy for the latent level of investor sentiment about climate change. This paper performs sentiment analysis on StockTwits posts related to climate change to proxy for investor climate sentiment. StockTwits was founded in 2008, and today is the largest social networking platform for investors and traders to share trading ideas and stock-related information.

In the remainder of this section, we first present arguments on the validity of the use of social network data to proxy for climate sentiment. Then, we describe the selection of StockTwits climate posts, and we present the computation of the sentiment score.

2.1 Climate Sentiment and Social Networks

Since investor sentiment cannot be observed, the literature has proposed different approaches to measure it. For instance, researchers have used market data (Baker and Wurgler, 2006), internet messages (Antweiler and Frank, 2004; Chen et al., 2014; Renault, 2017), news media data (Tetlock, 2007; Obaid and Pukthuanthong, 2022), Google searches of sentiment-revealing terms (Da et al., 2015), and company financial reports (Loughran and McDonald, 2011) to proxy for investor sentiment.

Recently, researchers have used news media data (Engle et al., 2020; Faccini et al., 2021; Ardia et al., 2022; Pástor et al., 2022), and Google Search Volume Index (SVI) (Choi et al., 2020; Ding et al., 2022) to measure perceived risk and attention on climate change. Behavioural finance models have proposed both investor sentiment and limited attention as explanations of stock prices under- and overreaction (De Long et al., 1990; Barberis et al., 1998; Hirshleifer and Teoh, 2003). However, sentiment and attention represent two different phenomena. Specifically, investor attention concerns how investors process information. For example, information that is presented in salient, easily processed form is generally absorbed more easily than information that is less salient, or that is only implicit in the public information set (Hirshleifer and Teoh, 2003). Differently, investor sentiment can be broadly defined as beliefs about the future that are not supported by facts (Baker and Wurgler, 2007). Investor sentiment depends on the investor information set (i.e., financial reports, news media articles), prior beliefs, and interaction with peers.

Our paper proposes the use of data from a social network platform, StockTwits, to measure investor climate sentiment. Investors rely on information transmitted through social interaction for financial advice and investment ideas (Brown et al., 2008; Hirshleifer and Teoh, 2009; Chen and Hwang, 2022). Furthermore, social interactions attract attention to freely available but less salient public information (Hu, 2022). Since most people do not have direct experience of climate change, we expect social interaction to be an important determinant of investors sentiment on climate change. Several works have proposed the use of Twitter to measure climate sentiment (Cody et al., 2015; Dahal et al., 2019; Loureiro and Alló, 2020). However, given that Twitter attracts a general audience, StockTwits is a less noisy data set to study the effects of climate sentiment on financial markets as its users are active investors (Sun et al., 2016).

2.2 Selection of StockTwits Climate Posts

StockTwits provided us with data on the universe of messages posted between January 1, 2010 and September 30, 2019. Then, among all the posts, we selected those related to climate change and global warming. In particular, we used the following search strings: 'climate change', 'global warming', 'emission', 'pollution', 'extreme weather', 'extreme temperature', and 'environmental'.

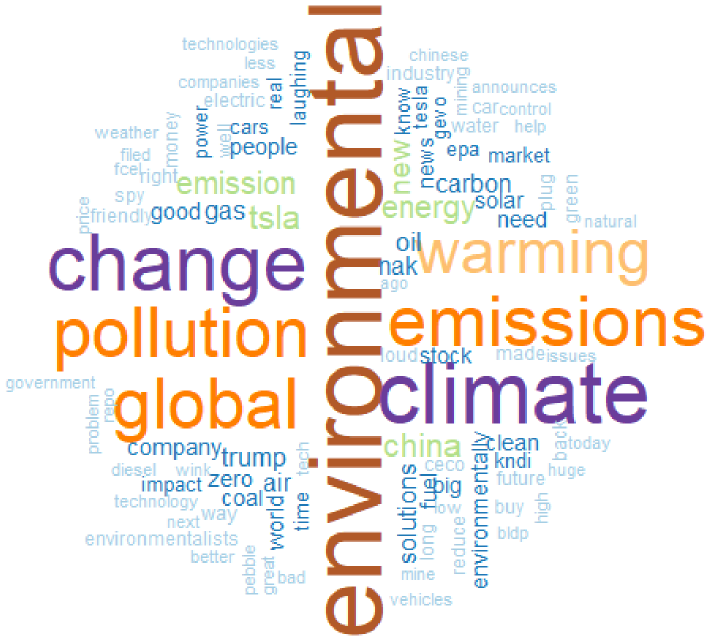
We started the search using only the search strings 'climate change' and 'global warming'. We decided to focus on both terms because they have been used interchangeably by news agencies despite their different meaning. Moreover, the general public may use one term in favour of the other given the topic in question, what they heard on the media or for a number of other reasons (Whitmarsh, 2009). Once we collected the posts containing the strings 'climate change' and 'global warming', we computed the correlation of the above strings with other words used in the posts. Among the words reporting the highest levels of correlation, we chose the strings included in the climate change vocabulary developed by Engle et al. (2020).[3] The selected strings included: 'emission', 'pollution', 'weather', 'temperature', 'environment', 'carbon' and 'energy'. To check the goodness of each search string, we run the search using the above search strings one-by-one. We realized that the words 'weather', 'temperature', 'energy', 'carbon' and 'environment' were often selecting posts not related to climate change. Hence, we decided to use the strings 'extreme weather' and 'extreme temperature' as these were used only in relation to climate issues. Similarly, we decided to use the adjective 'environmental' instead of the noun 'environment'. Furthermore, we decided to not use 'energy' and 'carbon' as search strings since they were capturing numerous irrelevant posts.[4]

Once we identified the posts according to the final set of search strings, we randomly selected a subset of posts and we manually checked whether we systematically included posts not discussing climate issues. We repeated the procedure several times. The final sample includes 43,445 climate posts sent by 12,364 unique StockTwits users.

[3] Engle et al. (2020) use twelve climate change white papers and fifty-nine climate change glossaries from various sources (e.g., United Nations, NASA, IPCC, Environmental Protection Agency, and the U.S. Global Change Research Program) to create the Climate Change Vocabulary.

[4] Table A.1 of the Appendix reports examples of posts with the excluded search strings.

Figure 1: Word cloud of StockTwits Posts on Climate issues



Notes: The figure presents the word cloud of the terms used in the StockTwits climate posts. Text size depends on the word frequency.

Figure 1 shows a word cloud of the StockTwits climate posts, the text size depends on how often the word appears in the posts. It is interesting to observe that, excluding the search strings, 'china' is one of the most frequent words. China is mainly mentioned because of either its high level of pollution, and poor environmental regulation or in relation to the manufacturing facilities in Shanghai of 'tesla' also referred to with its ticker symbol 'tsla'. The word 'energy' appears in relation to climate issues in the discussion on energy consumption and green energies. Not surprisingly another word that appears frequently is 'trump', U.S. former President Donald Trump contradictory and confusing position on climate change has been in the spotlight in several occasions. The ticker symbol of Northern Dinasty Minerals Ltd. ('nak') appears often in the discussion among environmentalists and climate change deniers on the environmental approval of its mining activities in Alaska. Furthermore, words related to fossil fuels such as 'oil', 'coal', and 'gas' are mentioned frequently in StockTwits climate posts.

Before introducing the computation of investor climate sentiment, we provide further evidence on the use of StockTwits to discuss climate issues. Since we expect that a higher public attention to climate issues can trigger interaction on these topics among investors, we compare the Google SVI of the topics 'climate change' and 'global warming' with

Table 1: Correlation matrix

	Attention to Climate Change	Attention to Global Warming
Attention to Climate Change (Google)	1.0000	
Attention to Global Warming (Google)	0.5244	1.0000
Social Interaction (StockTwits)	0.4918	0.4166

Notes: The table reports the correlation matrix of Attention to Climate Change (Google SVI of 'climate change'), Attention to Global Warming (Google SVI of 'global warming'), and Social Interaction (share of StockTwits climate related posts).

social interaction in StockTwits on climate issues which we define as follows:

$$SI = \frac{\#StockTwits\ Climate\ Posts}{\#StockTwits\ Posts}. \tag{1}$$

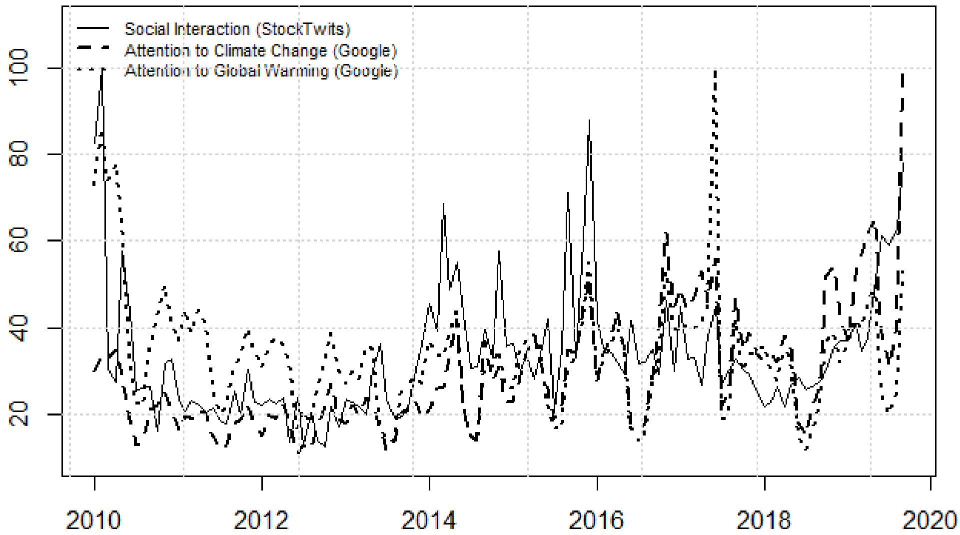
Similarly to the Google SVI, we give a value of 100 to the maximum observation in the series of social interaction and the other values are defined relative to the maximum. This variable can be considered a proxy for investor attention on climate change hence a comparison with Google SVI of climate change and global warming is meaningful as they measure public attention on these issues.

Table 1 reports the correlation between Google SVI of 'climate change' and 'global warming', and StockTwits social interaction about climate change. We observe that the correlation between social interaction in StockTwits and Google SVI of 'climate change' is 0.4918, while correlation with Google SVI of 'global warming' is 0.4166. These correlation coefficients can be considered high taking into account the specificity of each measure.

Figure 2 shows the time series of social interaction and Google SVI of 'climate change' and 'global warming'. We can observe that the three series generally follow a similar pattern. However, in some cases a peak in social interaction is not accompanied by a peak in attention to climate change and global warming. For instance, in March 2014 the Apple's CEO Tim Cook stated that climate change sceptic investors could sell their stocks if they did not support the Apple's attempt to cut greenhouse gas emission by investing in renewable energies. This statement boosted discussion on StockTwits but did not increase the Google SVI of 'climate change' and 'global warming'. Similarly, for the Volkswagen emissions scandal in September 2015, we observe a peak of social interaction in StockTwits but not in Google's searches. We consider this as an external validation of our sample of StockTwits climate posts.

Another concern with the sample of StockTwits climate posts is that they might mention only a small number of companies, hence the climate sentiment measure could reflect firm-specific sentiment rather than general climate sentiment of investors. Stock-

Figure 2: Social Interaction and Attention to Climate Change and Global Warming



Notes: The figure displays the time series of Social Interaction (share of StockTwits climate related posts), Attention to Climate Change (Google SVI of 'climate change'), and Attention to Global Warming (Google SVI of 'global warming').

twits users can post messages with a 'cashtag' followed by a stock ticker symbol (e.g., $AAPL) to link a message to a particular company. The sample of climate posts mention 1,838 unique tickers. In particular, 48.50% of messages mention a unique ticker, 45.30% of messages do not mention any ticker, and 6.20% of messages mention more than one ticker. In Table 14 of Appendix A.3, we report the 10 most frequent tickers that appears in posts that contain a unique ticker which can hence be directly linked to a specific stock. The three most frequent tickers are $TSLA, $NAK, and $GEVO, together they represent around 10% of the entire sample. Thus, the sentiment extracted from the sample of StockTwits climate posts is not firm-specific.[5]

2.3 Computation of the Sentiment Score

We perform sentiment analysis on the sample of StockTwits climate posts to measure investor climate sentiment.[6] Sentiment analysis is an increasing area of research and application, numerous textbooks illustrate the major algorithms to be used for this type of analyses (Feldman et al., 2007; Liu, 2015; Cambria et al., 2017). In this paper, we use

[5] As robustness test, we computed climate sentiment from the sample of StockTwits climate posts that do not mention the three most frequent tickers, $TSLA, $NAK, and $GEVO. We find that the main results of the paper still holds.

[6] Data on investor climate sentiment and social interaction from January 2010 to September 2019 are available from the author's website.

Table 2: Examples of Posts with Positive and Negative Sentiment Score

Sentence	Sentiment
Panel A: Positive Sentiment	
"I am not a Green New Deal person. We are just stating facts that EVs are more efficient and cheaper from a financial standpoint than gas, in the long term. If it saves money for fleets, while helping reduce pollution, and makes us all a lot of money in the process, Then I am all for it. Not sorry.	0.678
"I believe in human innovation. I believe we have the ability and the knowledge to care for our environment without plunging society into the dark ages. There are many companies implementing environmental-friendly practices [...]."	0.338
Panel B: Negative Sentiment	
"Oh you poor poor environmentalist.... you're so persecuted. Maybe you need a few signs and free money free everything to make up for it go vote for a socialist you loser"	-0.430
"They are mad about climate change today and will have a rally where they burn stuff and dump trash everywhere. Then they will shit in the streets because they are Woke"	-0.521

Notes: The table reports examples of posts with a positive (Panel A) and negative (Panel B) sentiment exchanged in StockTwits in September 2019.

the R package sentimentr (Rinker, 2019). The package sentimentr is designed to calculate text polarity sentiment in an accurate and quick way. The advantage of the package is the use of valence shifters, negators and amplifiers/deamplifiers, which respectively reverse, increase, and decrease the impact of a polarized word.

As a first step, we clean the text by replacing emoticons with their word equivalent through the replace_emoticon() command, so as to be included in the score computation, we convert all the text to lower case, we eliminate all mentions, and ashtags, we write all hyphanated words as two separate words, we remove punctuation and numbers, we remove all links, graphical and control characters. We utilize the combined and augmented version of Jockers (2017) and Rinker's augmented Hu and Liu (2004) positive/negative word list as sentiment lookup values. These dictionaries have been developed to summarize online opinions in reviews, tweets, blogs, and forum discussions. Since the polarity score is dependent upon the polarity dictionary used, we adapt the dictionary to our context. We refrain from using finance-specific dictionaries such as Henry's dictionary (Henry, 2008) because our goal is to measure the sentiment of investors on climate change rather than their sentiment on the market. The sentiment score is computed for each sentence and it is averaged out by month.[7]

Table 2 provides several examples of StockTwits posts classified as positive and negative sentiment. We observe that climate change is generally discussed with a negative tone by climate change sceptics and deniers, while climate change believers tend to use a more positive tone.

[7]More details on the sentiment analysis can be found in Section A.4 of the Appendix.

3 Data

In this section, we describe the data sources employed as well as the main variables adopted in our analysis.

3.1 Stock Information

We employ Refinitiv Eikon Datastream for financial data. We consider stocks traded in the two major U.S. financial markets, the New York Stock Exchange and Nasdaq. We apply several screening procedures for monthly returns. First, we follow Choi et al. (2020) and others in winsorizing percentage returns at the top and bottom 2.5% in each exchange in each month.[8] Moreover, similarly to Hou et al. (2011) and Ince and Porter (2006) we remove all monthly returns that are above 300% and reversed within 1 month, as well as zero monthly returns.[9]

We use both raw returns (not adjusted for risk) and risk-adjusted returns. We use the three-factor alphas as risk-adjusted returns. For each stock and each month we estimate the Fama-French three factors model (Fama and French, 1993) using daily data. The market excess return and returns of the SMB (Small minus Big) and HML (High minus Low) risk factors are retrieved from the Kenneth French's data library.[10]

We identify emission and clean stocks in two ways. First, we use the firm's industry. The Intergovernmental Panel on Climate Change (IPCC) identifies five major industry sectors as major emission sources: Energy; Transport; Buildings; Industry; and Agriculture, Forestry, and Other Land Use (AFOLU). Krey et al. (2014) include a full list of sectors subcategories. We manually match the Industry Classification Benchmark (ICB) codes available from Refinitiv Eikon Datastream with the IPCC category codes.[11] Following Choi et al. (2020), we classify all firms in the matched industries as emission (carbon-intensive) firms, the rest is classified as clean (low-emission) firms.

Second, we use firm's carbon emission data from Refinitiv ESG (formerly ASSET4). We use total CO_2 equivalent emissions and emission intensity. Total CO_2 equivalent

[8] As robustness test, we performed the analysis using winsorization at the top and bottom 1% and 5%. Results are available upon request and they confirm the main findings of the paper.

[9] If R_t or R_{t-1} is greater than 300% and $(1 + R_t)(1 + R_{t-1}) - 1 < 50\%$, then both R_t and R_{t-1} are removed. We remove zero monthly returns because Datastream repeats the last available data point for delisted firms.

[10] The Kenneth French's data library is available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[11] Appendix B contains a list of Industry Classification Benchmark (ICB) codes available from Refinitiv Eikon Datastream and the matching IPCC category codes which are classified as carbon intensive.

emissions are expressed in tonnes and they include both direct (scope 1) and indirect (scope 2) emissions. Refinitiv ESG follows green house gas (GHG) protocol for all their emission classifications by type. Emission intensity is computed as total CO_2 equivalent emissions divided by sales or revenues in USD millions. Emissions data are available for each firm annually since 2002. Refinitiv ESG identifies firms as ESG leaders (laggards) if they have an ESG score in the top (bottom) quartile of the distribution of ESG scores. Similarly, we identify a firm as emission (clean) if its total CO_2 equivalent emissions or emission intensity lies in the top (bottom) quartile of the distribution of total CO_2 equivalent emissions or emission intensity, respectively.

Throughout the paper, we primarily use IPCC definitions because they are available for all firms. Refinitiv ESG covers only a subset of firms, indeed we have data for only 1,048 stocks in our sample period to compute the returns of the EMC portfolio against 4,222 stocks when we use the IPCC definitions. Moreover, data from Refinitiv ESG may have a selection issue and the results should be interpreted with caution.[12]

Similarly to Choi et al. (2020), we compute the return of a long-short portfolio Emission-minus-Clean (EMC). The EMC portfolio buys a equal- or value-weighted portfolio of emission stocks and it sells a equal- or value-weighted portfolio of clean stocks.

3.2 Perceived Climate Change Risk and Concerns

We use the Media Climate Change Concerns index ($MCCC$) developed by Ardia et al. (2022) to measure concerns from news about climate change published by major U.S. newspapers and newswires. The index is available from January 2003 through June 2018.[13] The index is also available for different themes and topics. In what follows, we use the aggregate MCCC index, and the MCCC indeces of the news on the themes 'business impact' ($MCCC\_BI$), 'environmental impact' ($MCCC\_EI$), 'societal debate' ($MCCC\_SD$), and 'research' ($MCCC\_R$).

Another index is the EGKLS index (Engle et al., 2020) which is computed as the share of negative news on climate change in major outlets. The index measures perceived climate change risk and it is available from January 2008 through May 2018.[14]

[12] Refinitiv ESG collects data from a variety of sources including annual reports, company websites, corporate social responsibility reports, stock exchange filings, news sources and NGO websites. Refinitiv ESG do not cover all the U.S. public companies and the sample size increases from 417 in January 2010 to 989 in September 2019.

[13] We thank David Ardia for making these data available on his website.

[14] We thank Stefano Giglio and Johannes Stroebel for making these data available on their websites.

3.3 Temperatures and Severe Weather Events

We obtain monthly temperature data from the U.S. Climate Divisional Database,[15] and data on U.S. extreme weather events from the Severe Weather Data Inventory (SWDI).[16] The records in SWDI come from a variety of sources in the National Climatic Data Center (NCDC) archive.[17]

We follow Choi et al. (2020) in decomposing the series of U.S. temperature, frequency and damages of extreme weather events into a predictable seasonal component and an abnormal component. In particular, first we compute the average temperature of the U.S. in month t ($Temp_t$). Second, we compute the average temperature of the U.S. in the same calendar month in the previous 10 years ($MonTemp_t$). For example, $MonTemp_{Jan2010}$ is the average temperature of the U.S. in the month of January in the previous 10 years, that is from 2000 to 2009. The series of abnormal temperatures ($AbTemp$) is computed in the following way:

$$AbTemp_t = Temp_t - MonTemp_t, \tag{2}$$

We follow the same procedure to compute the series of abnormal number of extreme weather events ($AbEWE$):

$$AbEWE_t = EWE_t - MonEWE_t. \tag{3}$$

where EWE_t is the number of extreme weather events occurred in the U.S. in month t, and $MonEWE_t$ is the average number of extreme weather events occurred in the U.S. in the same calendar month in the previous 10 years.

Finally, the abnormal damages caused by extreme weather events in the U.S. in month

[15] Karl and Koss (1984) and Vose et al. (2014) describe the methodology used to compute temperatures in the U.S. Climate Divisional Database. Data can be retrieved from the following link: https://www.ncdc.noaa.gov/cag/national/time-series/110/tavg/all/1/1895-2020?base_prd=true&begbaseyear=2010&endbaseyear=2020.

[16] SWDI data can be accessed from the following link: https://www.ncdc.noaa.gov/ncdcs-severe-weather-data-inventory

[17] The weather events include: Astronomical Low Tide, Avalanche, Blizzard, Coastal Flood, Cold/Wind Chill, Debris Flow, Dense Fog, Dense Smoke, Drought, Dust Devil, Dust Storm, Excessive Heat, Extreme Cold/Wind, Chill, Flash Flood, Flood, Freezing Fog, Frost/Freeze, Funnel Cloud, Hail, Heat, Heavy Rain, Heavy Snow, High Surf, High Wind, Hurricane (Typhoon), Lake-Effect Snow, Lakeshore Flood, Lightning, Marine Hail, Marine High Wind, Marine Strong Wind, Marine Thunderstorm Wind, Rip Current, Seiche, Sleet, Storm Surge/Tide, Strong Wind, Thunderstorm Wind, Tornado, Tropical Depression, Tropical Storm, Tsunami, Volcanic Ash, Waterspout, Wildfire, Winter Storm, Winter Weather.

t ($AbDamages_t$) is computed as follows:

$$AbDamages_t = Damages_t - MonDamages_t, \quad (4)$$

where $Damages_t$ is the total damages caused by extreme weather events in the U.S. in month t. Note that this variable is not firm-specific. $MonDamages_t$ is the average damages caused by extreme weather events in the same calendar month in the previous 10 years. Since we need 10 years of data prior to January 2010 to compute the series of abnormal temperatures, frequency and damages of extreme weather events, we retrieve data from January 2000 to September 2019.

3.4 Events related to Climate Change and U.S. Environmental Policies

We build two dichotomous variables for international events related to climate change: i) $Conferences$ is equal to 1 when a UN climate change conference or summit takes place and it is equal to 0 otherwise; ii) *Reports* is equal to 1 when a report on climate change is released (i.e, IPCC summary reports, national climate assessment reports) and it is equal to 0 otherwise.

We also build a categorical variable for U.S. environmental policies (*Policies*). The variable *Policies* has a value of 1 if in that month the U.S. introduced an environmental policy such as the U.S. first Carbon Pollution Standard for New Power Plants; a value of -1 for either rollback or weakening of environmental policies such as the rollback of car emissions standards; and 0 otherwise. Information on U.S. environmental policies is retrieved from the Environment Protection Agency (EPA) website (EPA, 2019), and two National Geographic articles (National Geographic Staff, 2020, 2019).[18]

3.5 Carbon Price

We use the log of the settlement price of the ICE-ECX EUA futures as carbon price. The Carbon Emission Allowances (EUA) Futures Contract obliges each clearing member with a position open at cessation of trading for a contract month to make or take delivery of one lot of 1,000 EUA. Each EUA is an entitlement to emit one tonne of CO_2 equivalent gas. The settlement price of the ICE-ECX EUA futures is obtained from Refinitiv Eikon Datastream.

[18]A full list of events is available in Appendix C.

4 Empirical Results

The empirical analysis aims to investigate two questions: i) What are the determinants of investor climate sentiment? and ii) What is the relationship between investor climate sentiment and the stock price of carbon-intensive and low-emission firms?

4.1 Investor Climate Sentiment

Since investor climate sentiment computed as described in Section 2 may be capturing broader market sentiment, we orthogonolize it with respect to the overall sentiment of all StockTwits posts in any month. In particular, we estimate the following equation with OLS:

$$CSent_t = \alpha + \beta Sent_t + \epsilon_t, \tag{5}$$

where $CSent$ is the monthly climate sentiment (see Section 2), and $Sent$ is the monthly average of the sentiment score of all StockTwits posts. Then we compute the orthogonal climate sentiment as follows:

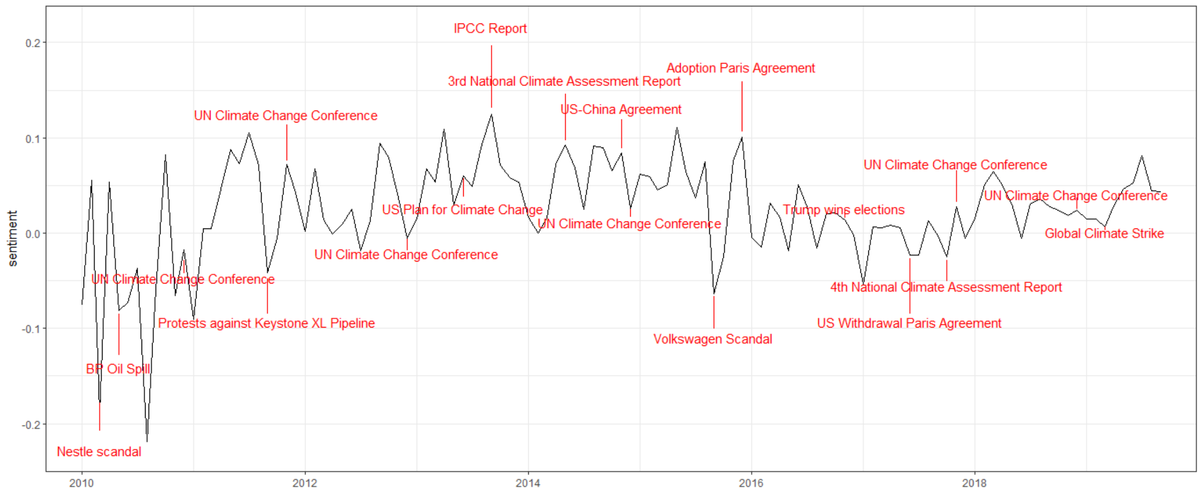
$$CSent_t^{\perp} = CSent_t - \hat{\beta} Sent_t, \tag{6}$$

where $\hat{\beta}$ is the OLS estimate of the slope coefficient in Eq. (5).

Figure 3 displays the monthly orthogonal investor climate sentiment score. We also report some major events related to climate change. During 2010, climate sentiment is mostly negative and it is highly volatile, the high volatility may be due to the lower number of posts available for that year.[19] From visual inspection of Figure 3, we observe that events such as the UN climate change conferences, IPCC reports, the National Climate Assessment reports, and international agreements on climate change (i.e., the Paris agreement and the US-China climate agreement) generally boost climate sentiment. On the contrary, environmental scandals, such as the BP oil spill and the Volkswagen's emission scandal, are generally associated with a drop in climate sentiment. Further, we record a steady decrease in climate sentiment from the months preceding the 2016 U.S. elections until the inauguration of the Trump's administration in January 2017. This is not surprising as in his presidential campaign, U.S. former President Donald Trump expressed his support to rescinding the Climate Action Plan and Waters of the U.S. rule,

[19] As robustness test, we performed the analysis excluding observations for 2010 from the sample. Results are confirmed and they are reported in Table 7.

Figure 3: Investor Climate Sentiment



Notes: The figure displays the monthly series of investor climate sentiment orthogonal to overall StockTwits sentiment from January 2010 to September 2019. We also report in red several major events related to climate change.

renewing the Keystone XL Pipeline project, canceling the Paris Climate Agreement, and reforming the regulatory environment.

Panel A of Table 3 shows the summary statistics for climate sentiment ($CSent^{\perp}$), social interaction in StockTwits on climate issues (SI), the aggregate Media Climate Change Concerns ($MCCC$) index, and the MCCC indeces of the news on the themes 'business impact' ($MCCC\_BI$), 'environmental impact' ($MCCC\_EI$), 'societal debate' ($MCCC\_SD$), and 'research' ($MCCC\_R$). Panel B of Table 3 reports the correlation matrix.

Investor climate sentiment can be seen as the result of the information on events related to climate change shared in traditional outlets such as newspapers, and interaction on these events in social media. Social media such as StockTwits are used to share opinions and ideas, as such users may change their views and sentiment following social interaction which can in turn affect asset pricing (Hirshleifer and Teoh, 2009; Shive, 2010; Chen and Hwang, 2022). We estimate the following regression equation to study the determinants of investor climate sentiment:

$$CSent_t^{\perp} = \alpha + \beta_1 SI_t + \beta_2 MCCC_t + \beta_3 SI_t \times MCCC_t + \epsilon_t. \tag{7}$$

Results are reported in Table 4. Columns 1 and 2 present the estimates of the model including only social interaction SI, and the aggregate $MCCC$ index respectively. The

Table 3: Investor Climate Sentiment and other variables

Panel A: Summary Statistics

Variable	Obs	Mean	St.Dev.	P10	P25	P50	P75	P90
CSent$^{\perp}$	117	0.0243	0.0537	-0.0297	-0.0001	0.0279	0.0602	0.0829
SI	117	33.7893	15.5334	20.4149	23.4727	30.3569	37.2177	56.1254
MCCC	102	1.1215	0.3083	0.7470	0.8990	1.0851	1.3112	1.5199
MCCC_BI	102	1.0009	0.2984	0.6638	0.7856	0.9684	1.1507	1.3740
MCCC_EI	102	1.0983	0.2983	0.7312	0.8685	1.0903	1.2800	1.5388
MCCC_SD	102	1.0823	0.4124	0.6264	0.7822	0.9882	1.3220	1.6213
MCCC_R	102	0.9637	0.2568	0.6862	0.7732	0.9387	1.1154	1.3440

Panel B: Correlation Matrix

	CSent$^{\perp}$	SI	MCCC	MCCC_BI	MCCC_EI	MCCC_SD	MCCC_R
CSent$^{\perp}$	1.0000						
SI	-0.0697	1.0000					
MCCC	0.0833	0.4467	1.0000				
MCCC_BI	0.0719	0.4909	0.9077	1.0000			
MCCC_EI	0.1130	0.2036	0.8193	0.5851	1.0000		
MCCC_SD	-0.0134	0.4303	0.9274	0.8192	0.6655	1.0000	
MCCC_R	0.2832	0.3813	0.7886	0.6045	0.7301	0.6659	1.0000

Notes: Panel A reports the summary statistics of investor climate sentiment and some other variables. CSent$^{\perp}$ is climate sentiment computed from StockTwits posts on climate change and global warming and orthogonalized to broader StockTwits market sentiment (see Eq. (6)). The computation of climate sentiment is described in Section 2. SI is the social interaction in StockTwits on climate issues, and it is computed according to Eq. (1). A value of 100 is given to the maximum value and the other observations are defined relative to the maximum. $MCCC$ is the aggregate Media Climate Change Concerns index developed by Ardia et al. (2022). The index is also available for different themes and topics. We consider the MCCC indeces of the news on the themes 'business impact' ($MCCC\_BI$), 'environmental impact' ($MCCC\_EI$), 'societal debate' ($MCCC\_SD$), and 'research' ($MCCC\_R$). Panel B reports the correlation matrix. The sample is from January 2010 to September 2019 for CSent$^{\perp}$ and SI, and from January 2010 to June 2018 for the MCCC indices.

coefficients are not significant meaning that neither SI nor $MCCC$ can explain investor climate sentiment alone. Column 3 contains the results of the model with the interaction term. Both SI and $MCCC$ have a significantly negative coefficient at respectively 1% and 10% confidence level, and the interaction term is significantly positive at 1% confidence level. This means that when social interaction is low (below $0.0563/0.2189 = 0.2572$), concerns on climate change are negatively associated with climate sentiment. When social interaction increases the relationship becomes positive. As more and more investors share their opinions on climate change, they influence each other views and when news on climate change arise they tend to discuss them with a more positive sentiment. This is consistent with a relative reduction of climate change deniers which are more prone to use negative tones as compared to climate change believers. To further investigate the determinants of investor climate sentiment, we analyse the effect of the news on four different themes related to climate change. In Column 4, we consider the news on the business impact of climate change, such as news on climate legislation, carbon tax, and carbon reduction technologies. We can observe that $MCCC\_BI$ has a negative direct impact on climate sentiment although not significant, and the interaction term is significantly positive (1% confidence level). Hence, if there is social interaction on climate change,

Table 4: Determinants of Investor Climate Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0316*	0.0058	0.1029***	0.0791**	0.1022**	0.1106***	0.0905**
	(0.0165)	(0.0306)	(0.0390)	(0.0350)	(0.0499)	(0.0348)	(0.0430)
SI	−0.0263		−0.3111***	−0.2244***	−0.3205**	−0.2710***	−0.4082***
	(0.0411)		(0.0775)	(0.0768)	(0.1239)	(0.0832)	(0.0867)
MCCC		0.0154	−0.0563*				
		(0.0244)	(0.0335)				
MCCC×SI			0.2189***				
			(0.0488)				
MCCC_BI				−0.0392			
				(0.0328)			
MCCC_BI×SI				0.1615***			
				(0.0454)			
MCCC_EI					−0.0648*		
					(0.0385)		
MCCC_EI×SI					0.2625***		
					(0.0944)		
MCCC_SD						−0.0694**	
						(0.0317)	
MCCC_SD×SI						0.1999***	
						(0.0571)	
MCCC_R							−0.0406
							(0.0447)
MCCC_R×SI							0.3180***
							(0.0795)
Obs.	102	102	102	102	102	102	102
Adj. R^2	-0.0051	-0.0030	0.0447	0.0237	0.0444	0.0351	0.1583
AIC	-290.3190	-290.5328	-293.5609	-291.3471	-293.5342	-292.5470	-306.4776
BIC	-282.4441	-282.6579	-280.4360	-278.2222	-280.4094	-279.4221	-293.3527

Notes: This table reports the estimates of Eq. (7). The dependent variable is $\text{CSent}^{\perp}$. See note of Table 3 for variables definition. The sample is from January 2010 to June 2018. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

$MCCC\_BI$ is positively associated with climate sentiment and its impact increases as social interaction rises. In Column 5, we consider the news on the environmental impact of climate change, such as news on extreme temperatures, forests, glaciers, and ecosystems. We find that $MCCC\_EI$ has a negative direct impact on climate sentiment (10% confidence level). Moreover, the interaction term is significantly positive (1% confidence level). Specifically, when social interaction is low (below $0.0648/0.2625 = 0.2469$), $MCCC\_EI$ is negatively associated with climate sentiment and the sign of the relationship is reversed when social interaction is higher. In Column 6, we consider the news on the societal debate on climate change, such as news on political campaign, social events, and controversies. We show that $MCCC\_SD$ has a negative direct impact on climate sentiment (5% confidence level). Moreover, when social interaction is low (below $0.0694/0.1999 = 0.3472$), $MCCC\_SD$ is negatively associated with climate sentiment and the sign of the relationship is reversed when social interaction is higher. In the last column, we consider the news on the research on climate change, such as news on

UN/IPCC reports, and scientific studies. We find that $MCCC\_R$ has not a significant direct impact on climate sentiment, but if there is social interaction on the matter, climate sentiment increases as $MCCC\_R$ increases and its impact significantly increases as social interaction rises.

Summing up, when social interaction is low, investor climate sentiment tends to be more negative when there is an increase in concerns on the environmental impact of climate change and there are more news on the societal debate about climate change. The opposite is observed when social interaction is higher. Furthermore, investor climate sentiment tends to be more positive when there is an increase in the concerns on the business impact of climate change and new research on climate change is released as long as there is social interaction on the matter.

4.2 Stock Returns and Investor Climate Sentiment

In this section, we examine the relationship between investor climate sentiment and stock prices. Portfolio *Emission* includes all firms whose Industry Classification Benchmark (ICB) is matched with the IPCC sectors. All remaining firms are assigned to portfolio *Clean*. A long-short portfolio EMC (Emission Minus Clean) is formed by buying *Emission* and selling *Clean*. Panel A of Table 5 shows the summary statistics for equally-weighted portfolios, and Panel B for value-weighted portfolios. Risk-adjusted return equals the three-factor alpha, for each stock for each month we estimate the intercept of the Fama-French three factors model (Fama and French, 1993) using daily data. Then, we run the following regressions:

$$\begin{aligned} r_t =& \alpha + \beta CSent^{\perp}_{t-1} + \epsilon_t \\ r_t =& \alpha + \beta_1 CSent^{\perp}_{t-1}\,Q2 + \beta_2 CSent^{\perp}_{t-1}\,Q3 + \beta_3 CSent^{\perp}_{t-1}\,Q4 + \\ & \beta_4 CSent^{\perp}_{t-1}\,Q5 + \epsilon_t \end{aligned} \tag{8}$$

where r_t is the equal-weighted or value-weighted, risk-adjusted or raw return (not adjusted for risk) of either the EMC, *Emission*, or *Clean* portfolios in month t. $CSent^{\perp}$ is the investor climate sentiment computed as described in Section 2 and then orthogonalized to StockTwits broader market sentiment. $CSent^{\perp}$ $Q2$-$Q5$ denote quintile dummies with respect to the orthogonal investor climate sentiment.

Figure 4 displays the average equal-weighted EMC risk-adjusted returns conditional on investor climate sentiment quintiles with the 95% confidence intervals. We observe that EMC returns tend to decrease as we move up the climate sentiment quintiles, with

Table 5: Emission-minus-clean portfolio return

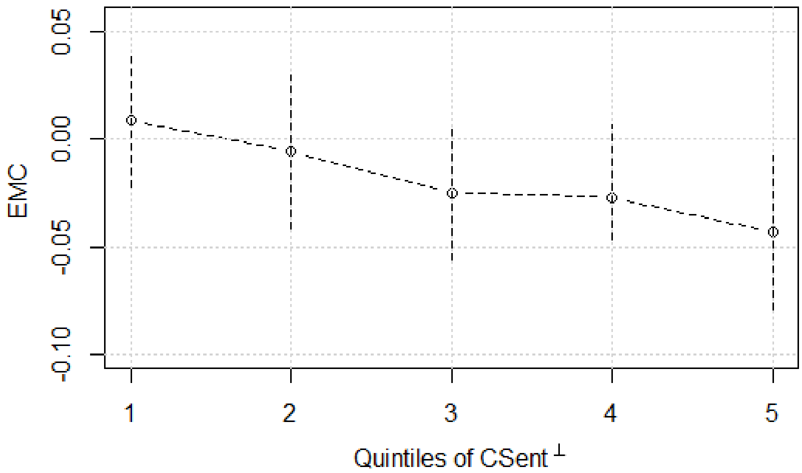
Variable	Obs	Mean	St.Dev.	P10	P25	P50	P75	P90
Equal-weighted								
EMC	117	-0.0171	0.0758	-0.1207	-0.0728	-0.0104	0.0335	0.0796
EMC (raw)	117	-0.2331	2.1774	-2.6029	-1.7562	-0.5339	0.9945	2.2898
Clean	117	-0.0028	0.0361	-0.0485	-0.0243	-0.0040	0.0189	0.0381
Clean (raw)	117	0.8621	3.3190	-3.6683	-0.3935	1.1974	2.9949	4.4917
Emission	117	-0.0199	0.0719	-0.1098	-0.0617	-0.0178	0.0298	0.0724
Emission (raw)	117	0.6290	3.6614	-4.3185	-1.0683	1.0948	2.7572	4.6018
Value-weighted								
EMC	117	-0.0136	0.0859	-0.1243	-0.0797	-0.0152	0.0611	0.1032
EMC (raw)	117	-0.1786	1.9872	-2.7947	-1.3687	-0.1341	0.9016	2.1277
Clean	117	0.0013	0.0250	-0.0296	-0.0093	0.0023	0.0127	0.0323
Clean (raw)	117	1.0512	2.8932	-2.4703	-0.4271	1.0531	2.8701	4.2448
Emission	117	-0.0123	0.0824	-0.1205	-0.0726	-0.0049	0.0579	0.0853
Emission (raw)	117	0.8726	3.6952	-3.6591	-0.9746	1.0158	2.6984	4.9880

Notes: The table reports the summary statistics of the emission-minus-clean (EMC) portfolio. Emission and Clean portfolios are formed based on firms' industry classification. Carbon-intensive industries are defined following the IPCC's report. Portfolio percentage return equals the equal- or value-weighted average risk adjusted return of stocks at month t. Adjusted return equals the three-factor alpha. For each stock for each month we estimate the intercept of the Fama-French three factors model (Fama and French, 1993) using daily data. EMC equals Emission minus Clean. EMC (raw) is calculated using raw returns (not adjusted for risk), it equals Emission (raw) minus Clean (raw). The sample is from February 2010 to October 2019.

statistically significant underperformance in the highest quintiles.

Table 6 presents the results. Column 1 of Panel A shows that higher investor climate sentiment is associated with significantly lower EMC risk-adjusted returns. A 1-standard-deviation increase in $CSent^{\perp}$ corresponds to a decrease of 1.41 bps in EMC return ($= -0.2633 \times 0.0537$). Column 2 replaces $CSent^{\perp}$ with the quintile dummies based on investor climate sentiment. We show that the negative effect on EMC returns is the strongest in the highest climate sentiment quintile with a change from climate sentiment quintile 1 (most negative) to quintile 5 (most positive) corresponding to a drop of 5.19 bps in risk-adjusted return (10% confidence level). We obtain similar results when we consider raw returns (Columns 3 and 4). In the last two columns, we focus on the effect of investor climate sentiment on the risk-adjusted returns of the portfolios $Clean$ and $Emission$, respectively. Relative to the bottom quintile of investor climate sentiment, $Emission$ earns 7.17 bps less in risk-adjusted returns in the top quintile at the 1% confidence level. The difference in the returns of the $Clean$ portfolio between the bottom and top quintile of investor climate sentiment is 1.98 bps (5% confidence level). When we consider value-weighted returns in Panel B, the difference in the returns of the $Clean$ portfolio between the bottom and top quintile of investor climate sentiment is statistically insignificant. Hence, the low EMC returns in the months with high investor climate sentiment is mainly driven by the $Emission$ portfolio. This evidence is consistent with

Figure 4: EMC Return and Quintiles of Investor Climate Sentiment



Notes: The figure presents the average equal-weighted EMC adjusted percentage returns (vertical axis) conditional on $CSent^{\perp}$ quintiles (horizontal axis) with 95% confidence intervals.

investors selling stocks in carbon-intensive industries when climate sentiment is more positive. Baker and Wurgler (2007) show that stocks which are hard to value are most affected by sentiment. Thus, given the high subjective valuation of firms' environmental impact, emission stocks are likely to be most sensitive to climate sentiment-based demand.

Note that for space constraints, in what follows we report only results for equally-weighted portfolios. Results for value-weighted portfolios are similar and they are available upon request.

A concern about the IPCC industry classification is that we may wrongly classify a firm as emission because of its industry while according to its level of CO_2 equivalent emissions that firm should be treated as clean. In alternative specifications, we use both total CO_2 equivalent emissions and emission intensity[20] from Refinitiv ESG to define emission and clean stocks. This analysis is performed with a smaller sample of stocks (1,048 stocks) as Refinitiv ESG covers only a subset of firms. Columns 1 and 2 of Table 7 use total CO_2 equivalent emissions to define emission and clean stocks, while Columns 3 and 4 use emission intensity. Results are in line with those of our previous table. EMC earns lower returns when investor climate sentiment is more positive. Concerning the magnitude of the coefficients, in Column 1, a 1-standard-deviation increase in $CSent^{\perp}$ corresponds to a decrease of 1.56 bps in EMC risk-adjusted returns which is similar to

[20]Emission intensity allows to take into account the concerns presented in Aswani et al. (2022) that the relationship between emission and returns hold only with unscaled emissions.

Table 6: EMC Return and Investor Climate Sentiment

Panel A: Equal-weighted EMC returns	(1)	(2)	(3)	(4)	(5)	(6)
	EMC		EMC (raw)		Clean	Emission
Constant	-0.0107	0.0084	0.0652	0.9013***	0.0068	0.0152
	(0.0066)	(0.0149)	(0.1850)	(0.3188)	(0.0074)	(0.0118)
$\text{CSent}^{\perp}_{t-1}$	-0.2633**		-12.2740***			
	(0.1184)		(2.7883)			
$\text{CSent}^{\perp}_{t-1}$ Q2		-0.0142		-1.1822***	-0.0117	-0.0259
		(0.0209)		(0.4415)	(0.0099)	(0.0167)
$\text{CSent}^{\perp}_{t-1}$ Q3		-0.0332*		-1.2112**	-0.0106	-0.0438**
		(0.0196)		(0.4851)	(0.0105)	(0.0177)
$\text{CSent}^{\perp}_{t-1}$ Q4		-0.0283		-1.3536***	-0.0056	-0.0340**
		(0.0199)		(0.5165)	(0.0096)	(0.0151)
$\text{CSent}^{\perp}_{t-1}$ Q5		-0.0519*		-1.9392***	-0.0198**	-0.0717***
		(0.0265)		(0.5024)	(0.0089)	(0.0248)
Obs.	117	117	117	117	117	117
Adj. R^2	0.0265	0.0215	0.0838	0.0542	-0.0001	0.0773

Panel B: Value-weighted EMC returns	(1)	(2)	(3)	(4)	(5)	(6)
	EMC		EMC (raw)		Clean	Emission
Constant	-0.0041	0.0265*	0.1143	1.0715***	0.0004	0.0269*
	(0.0081)	(0.0160)	(0.1884)	(0.3375)	(0.0081)	(0.0137)
$\text{CSent}^{\perp}_{t-1}$	-0.3913***		-12.0529***			
	(0.1361)		(2.9404)			
$\text{CSent}^{\perp}_{t-1}$ Q2		-0.0325		-1.0543**	0.0016	-0.0309
		(0.0230)		(0.4776)	(0.0083)	(0.0214)
$\text{CSent}^{\perp}_{t-1}$ Q3		-0.0441**		-1.5058***	0.0003	-0.0438**
		(0.0217)		(0.4669)	(0.0099)	(0.0214)
$\text{CSent}^{\perp}_{t-1}$ Q4		-0.0520**		-1.7435***	0.0043	-0.0477**
		(0.0232)		(0.4696)	(0.0087)	(0.0198)
$\text{CSent}^{\perp}_{t-1}$ Q5		-0.0723***		-1.9699***	-0.0016	-0.0739***
		(0.0261)		(0.4569)	(0.0094)	(0.0248)
Obs.	117	117	117	117	117	117
Adj. R^2	0.0517	0.0470	0.0984	0.0953	-0.0291	0.0558

Notes: This table reports the results of the analysis of the link between EMC portfolio returns and investor climate sentiment. Panel A reports the results of regressions of EMC on lagged climate sentiment using equal-weighted portfolio returns, and panel B uses value-weighted returns. Columns 2, 4, 5 and 6 replaces $CSent^{\perp}$ with the quintile dummies ($CSent^{\perp}Q2 - Q5$) based on investor climate sentiment. The sample is from February 2010 to October 2019 for EMC returns and from January 2010 to September 2019 for investor climate sentiment. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

what we find with the IPCC industry classifications. In Column 3, the coefficient is larger, in particular a 1-standard-deviation increase in $CSent^{\perp}$ corresponds to a decrease of 2.14 bps in EMC risk-adjusted returns.

Columns 5 to 8 of Table 7 contain another robustness check. Some carbon-intensive industries' returns may be correlated with fluctuations in oil prices (Hsu et al., 2022). Columns 5 and 6 include in the Emission portfolio only Energy firms (IPCC Energy sector), while Columns 7 and 8 include in the Emission portfolio firms in the other four carbon-intensive industries according to IPCC (Transport, Buildings, Industry and

Table 7: EMC Return and Investor Climate Sentiment: Robustness Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total Emissions		Emission Intensity		Energy		Non-Energy		Jan 2011 - Sept 2019	
Constant	-0.0065	0.0106	-0.0041	0.0219	-0.0130	0.0524^{**}	-0.0095	0.0023	-0.0086	0.0044
	(0.0079)	(0.0181)	(0.0107)	(0.0226)	(0.0103)	(0.0212)	(0.0066)	(0.0104)	(0.0091)	(0.0211)
$\text{CSent}^{\perp}_{t-1}$	-0.2907^{**}		-0.3987^{**}		-0.7507^{***}		-0.2464^{***}		-0.3334^{*}	
	(0.1337)		(0.1738)		(0.2554)		(0.0878)		(0.1976)	
$\text{CSent}^{\perp}_{t-1}$ Q2		0.0044		-0.0080		-0.0721^{**}		-0.0093		-0.0101
		(0.0295)		(0.0311)		(0.0295)		(0.0180)		(0.0256)
$\text{CSent}^{\perp}_{t-1}$ Q3		-0.0332		-0.0472		-0.0982^{***}		-0.0246		-0.0292
		(0.0263)		(0.0328)		(0.0351)		(0.0181)		(0.0251)
$\text{CSent}^{\perp}_{t-1}$ Q4		-0.0367		-0.0429		-0.1144^{***}		-0.0055		-0.0190
		(0.0257)		(0.0326)		(0.0408)		(0.0165)		(0.0246)
$\text{CSent}^{\perp}_{t-1}$ Q5		-0.0551^{**}		-0.0799^{**}		-0.1350^{***}		-0.0488^{**}		-0.0533^{*}
		(0.0266)		(0.0356)		(0.0473)		(0.0195)		(0.0308)
Obs.	117	117	117	117	117	117	117	117	105	105
Adj. R^2	0.0193	0.0266	0.0225	0.0241	0.0668	0.0715	0.0294	0.0353	0.0206	0.0177

Notes: The table presents several robustness tests of the results in Table 6. In Columns 1 and 2, stocks are defined as emission (clean) stocks if their total CO_2 equivalent emissions are in the top (bottom) quartile of the distribution of total CO_2 equivalent emissions. In Columns 3 and 4, stocks are defined as emission (clean) stocks if their emission intensity is in the top (bottom) quartile of the distribution of emission intensity. In Columns 5 and 6, the Emission portfolio contains Energy firms. In Columns 7 and 8, the Emission portfolio contains carbon-intensive industries according to IPCC which are non-energy firms. In Columns 9 and 10 we exclude observations referring to 2010 since the computation of investor climate sentiment in 2010 is based on a lower number of StockTwits posts than in the following years. All portfolio returns are calculated using the equal-weighted average of risk-adjusted returns. See Table 6 for a definition of $\text{CSent}^{\perp}$ Q2-Q5. The sample of the regression in Columns 1 to 6 is from February 2010 to October 2019 for EMC returns and from January 2010 to September 2019 for investor climate sentiment. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

AFOLU). We find that both groups earn lower returns when investor climate sentiment is more positive. The results for non-energy carbon-intensive industries confirm that the findings are not merely driven by oil prices.

A further concern regards the quality of the estimates of investor climate sentiment in the first sampled year as it is based on a lower number of StockTwits posts. In Columns 9 and 10 of Table 7, we exclude the first year of observations from the sample leaving us with data from January 2011 to September 2019. Results show that the evidence holds also in the shorter sample.

4.3 Understanding the pricing effect

Behavioural finance models predict that investor sentiment can drive prices away from fundamentals (De Long et al., 1990) and because of limits to arbitrage, the mispricing might last for awhile (Pontiff, 1996; Shleifer and Vishny, 1997). Nonetheless, rational investors will take advantage of the mispricing until it will disappear. When investor climate sentiment is more positive, irrational investors may decrease their relative demand for emission stocks driving prices away from fundamentals. However, over time as investors learn, prices should correct. Hence, investor climate sentiment should predict return reversal. We examine the relationship between investor climate sentiment and long-term returns of the EMC portfolio.

$$\begin{aligned} EMC_{t,t+k} =& \alpha + \beta CSent^{\perp}_{t-1} + \epsilon_t, \\ EMC_{t,t+k} =& \alpha + \beta_1 CSent^{\perp}_{t-1}\,Q2 + \beta_2 CSent^{\perp}_{t-1}\,Q3 + \beta_3 CSent^{\perp}_{t-1}\,Q4 + \\ & \beta_4 CSent^{\perp}_{t-1}\,Q5 + \epsilon_t, \end{aligned} \tag{9}$$

where $k = \{12, 18, 24\}$, and $EMC_{t,t+k}$ are the equal-weighted risk-adjusted returns from month t to month $t + k$. A decrease of the absolute magnitude of the β coefficient with longer-term returns implies that part of the investor reaction to climate sentiment was irrational as it led to price reversal. Differently, if the absolute magnitude of the β coefficient appears stable or increasing with longer-term returns, this can be interpreted as return continuation and slow belief updating (Barberis et al., 1998).

Table 8 reports the estimates of Eq. (9). The estimate of the coefficient of CSent$^{\perp}$ in Column 1 is significantly negative at 10% confidence level. A 1-standard-deviation increase in CSent$^{\perp}$ corresponds to a decrease of 1.41 bps in EMC return after one month (see Table 6) and 0.46 bps after one year. Further, we find that the effect of investor climate sentiment on EMC returns eventually revert back to zero after 18 and 24 months (Columns 3 and 5). We find similar results when we use climate sentiment quintiles to explain long-term EMC returns. These findings indicate that there is some degree of reversal in beliefs.

Next, we study whether salient but uninformative events such as UN conferences on climate change, reports, and abnormal weather events, can help to correct the mispricing induced by irrational investors trading on climate sentiment. Because of investors limited attention (Hirshleifer and Teoh, 2003), the effect of investor climate sentiment on EMC returns may depend on the level of attention on climate related issues.

In Table 9, we study the effect of attention-grabbing events such as UN conferences and summits on climate change ($Conferences$), the release of a report on climate change ($Reports$), and high variations in perceived climate risk ($EGKLS$). The variable $EGKLS$ is equal to 1 when the EGKLS index is above its median. Columns 1 and 2 show that EMC returns reaction to investor climate sentiment does not change when a UN conference or summit takes place. Column 3 reports that EMC returns react positively to investor climate sentiment in the months in which there is the release of a report on climate change, meaning that these reports contribute to the investor learning process

Table 8: Long-term EMC Return and Investor Climate Sentiment

	(1)	(2)	(3)	(4)	(5)	(6)
	$EMC_{t,t+12}$		$EMC_{t,t+18}$		$EMC_{t,t+24}$	
Constant	-0.0160^{**}	-0.0100	-0.0166^{*}	-0.0132^{**}	-0.0163	-0.0157^{**}
	(0.0077)	(0.0072)	(0.0093)	(0.0057)	(0.0106)	(0.0066)
$\text{CSent}_{t-1}^{\perp}$	-0.0862^{*}		-0.0451		-0.0270	
	(0.0498)		(0.0428)		(0.0575)	
$\text{CSent}_{t-1}^{\perp}$ Q2		-0.0131^{**}		-0.0091		-0.0026
		(0.0055)		(0.0060)		(0.0041)
$\text{CSent}_{t-1}^{\perp}$ Q3		-0.0094^{*}		-0.0042		0.0019
		(0.0053)		(0.0044)		(0.0042)
$\text{CSent}_{t-1}^{\perp}$ Q4		-0.0024		0.0025		0.0006
		(0.0059)		(0.0059)		(0.0078)
$\text{CSent}_{t-1}^{\perp}$ Q5		-0.0156^{*}		-0.0114^{*}		-0.0059
		(0.0079)		(0.0062)		(0.0055)
Obs.	117	117	117	117	117	117
Adj. R^2	0.0366	0.0448	0.0110	0.0613	0.0005	-0.0003

Notes: This table reports the results of regressions of $EMC_{t,t+12}$, $EMC_{t,t+18}$, and $EMC_{t,t+24}$ on investor climate sentiment at time $t-1$. All EMC returns are calculated using the equal-weighted average of risk-adjusted returns. The sample is from February 2010 to October 2019 for EMC returns and from January 2010 to September 2019 for investor climate sentiment. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

and correction of mispricing. Column 4 presents a similar evidence in the top $CSent^{\perp}$ quintile. In Column 6 we show that the impact of the top $CSent^{\perp}$ quintile on EMC returns is weaker when perceived climate change risk is above its median.

Choi et al. (2020) show that people revise their beliefs about climate change upwards when experiencing abnormal temperatures, hence abnormal weather may contribute to the correction of the mispricing of the EMC portfolio induced by irrational investors trading on climate sentiment. In Table 10 we study the effect of abnormally high temperatures ($Temp\_High$), abnormally high number of extreme weather events (EWE_High) and abnormally high damages caused by extreme weather events ($Damages\_High$) on the impact of investor climate sentiment on stock prices. $Temp\_High$ is equal to 1 when $AbTemp$, computed according to Eq. (2), is above its sample median. Similarly, EWE_High and $Damages\_High$ are equal to 1 when $AbEWE$ and $AbDamages$, computed according to Eq. (3) and (4), are above their sample median. Addoum et al. (2021) show that firms whose earnings are the most affected by temperatures shocks do not necessarily operate in carbon-intensive industries according to IPCC. Thus, both emission and clean stocks can suffer from negative earnings shocks following high temperatures. As a result EMC returns should not be statistically different in warmer months. Nevertheless, in Columns 1 and 2 we document two effects of abnormally warm temperatures on EMC returns. First, consistent with Choi et al. (2020), we find that EMC returns are significantly lower in abnormally warm months. Second, the interaction term

Table 9: EMC Return and Investor Climate Sentiment: Attention-grabbing events

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.0122*	0.0065	−0.0105	0.0090	−0.0050	0.0153
	(0.0067)	(0.0154)	(0.0068)	(0.0148)	(0.0106)	(0.0152)
$\text{CSent}^{\perp}_{t-1}$	−0.2778***		−0.3092**		−0.4237***	
	(0.1003)		(0.1332)		(0.1248)	
Conferences	0.0132	0.0236				
	(0.0318)	(0.0207)				
$\text{CSent}^{\perp}_{t-1}$ × Conferences	0.1700					
	(1.2021)					
Reports			−0.0244	−0.0144		
			(0.0286)	(0.0276)		
$\text{CSent}^{\perp}_{t-1}$ × Reports			0.7722***			
			(0.2907)			
EGLKS					−0.0099	−0.0163
					(0.0174)	(0.0174)
$\text{CSent}^{\perp}_{t-1}$ × EGKLS					0.2550	
					(0.2379)	
$\text{CSent}^{\perp}_{t-1}$ Q2		−0.0133		−0.0142		−0.0116
		(0.0210)		(0.0209)		(0.0227)
$\text{CSent}^{\perp}_{t-1}$ Q3		−0.0354*		−0.0326*		−0.0185
		(0.0197)		(0.0193)		(0.0205)
$\text{CSent}^{\perp}_{t-1}$ Q4		−0.0284		−0.0283		−0.0365*
		(0.0199)		(0.0197)		(0.0206)
$\text{CSent}^{\perp}_{t-1}$ Q5		−0.0497**		−0.0604**		−0.0935***
		(0.0218)		(0.0300)		(0.0222)
$\text{CSent}^{\perp}_{t-1}$ Q5× Conf.		−0.0259				
		(0.1290)				
$\text{CSent}^{\perp}_{t-1}$ Q5 × Reports				0.0776*		
				(0.0410)		
$\text{CSent}^{\perp}_{t-1}$ Q5 × EGKLS						0.0705*
						(0.0372)
Obs.	117	117	117	117	101	101
Adj. R^2	0.0155	0.0107	0.0253	0.0218	0.0232	0.0470

Notes: The table reports the results of regressions of EMC on the interaction of lagged climate sentiment with *Conferences* (Columns 1 and 2), *Reports* (Columns 3 and 4), and *EGKLS* (Columns 5 and 6). *Conferences* is a dummy variable for UN conferences on climate change, *Reports* is a dummy variable for the release of a report on climate change, *EGKLS* is a dummy variable for above median variations in negative climate change news. The sample is from February 2010 to October 2019 for EMC returns and from January 2010 to September 2019 for investor climate sentiment and the other variables. The sample is reduced in Columns 5 and 6 because the EGKLS' measure is available only through May 2018. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

$CSent^{\perp} \times Temp\_High$ is significantly (1% confidence level) positive and it is larger than the coefficient of $CSent^{\perp}$. This suggests that irrational investors will decrease their relative demand for emission stocks when climate sentiment is more positive creating a mispricing in the EMC portfolio. However, when temperatures are abnormally warm investors will trade to correct the mispricing. We obtain similar results with climate sentiment quintiles. Moreover, we document that the effect of investor climate sentiment on EMC returns is either positive or negative but weaker when the number of abnormal extreme weather events and the abnormal damages caused by extreme weather events are respectively above their median (Columns 3-6). We do not find any significant direct

Table 10: EMC Return and Investor Climate Sentiment: Weather

	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0036	0.0260*	0.0045	0.0219	−0.0038	0.0195
	(0.0103)	(0.0133)	(0.0128)	(0.0179)	(0.0100)	(0.0139)
$\text{CSent}^{\perp}$	−0.5934***		−0.7081***		−0.3421*	
	(0.1514)		(0.2211)		(0.1981)	
Temp_High	−0.0275**	−0.0324**				
	(0.0139)	(0.0142)				
$\text{CSent}^{\perp}\times$ Temp_High	0.6962***					
	(0.2374)					
EWE_High			−0.0234	−0.0230		
			(0.0165)	(0.0152)		
$\text{CSent}^{\perp}\times$ EWE_High			0.7154**			
			(0.3003)			
Damages_High					−0.0139	−0.0241
					(0.0167)	(0.0149)
$\text{CSent}^{\perp}\times$Damages_High					0.1663	
					(0.2893)	
$\text{CSent}^{\perp}$ Q2		−0.0163		−0.0176		−0.0106
		(0.0187)		(0.0195)		(0.0220)
$\text{CSent}^{\perp}$ Q3		−0.0296		−0.0376**		−0.0317
		(0.0182)		(0.0181)		(0.0196)
$\text{CSent}^{\perp}$ Q4		−0.0318*		−0.0287		−0.0289
		(0.0169)		(0.0202)		(0.0199)
$\text{CSent}^{\perp}$ Q5		−0.0952***		−0.0961***		−0.0820***
		(0.0243)		(0.0282)		(0.0308)
$\text{CSent}^{\perp}$ $Q5\times$Temp_High		0.1010**				
		(0.0431)				
$\text{CSent}^{\perp}$ $Q5\times$EWE_High				0.0846**		
				(0.0337)		
$\text{CSent}^{\perp}$ $Q5\times$Damages_High						0.0658*
						(0.0335)
Obs.	117	117	117	117	117	117
Adj. R^2	0.0765	0.0832	0.0727	0.0587	0.0172	0.0411

Notes: The table reports the results of regressions of EMC on the interaction of lagged climate sentiment with above median abnormal temperatures (*Temp_High*), above median number of abnormal extreme weather events (*EWE_High*), and above median abnormal damages (USD billions) caused by extreme weather events (*Damages_High*). The sample is from February 2010 to October 2019 for EMC returns and from January 2010 to September 2019 for investor climate sentiment and the other variables. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

effect of *EWE_High* and *Damages_High* on EMC returns. This is consistent with Choi et al. (2020) which show that EMC returns do not respond to abnormal weather events other than temperatures.

Finally, in Table 11 we study the effect of investor climate sentiment on stock prices when carbon prices are high (Columns 1 and 2), and when an environmental policy is introduced or rolled back in the U.S. (Columns 3 and 4).[21] *carbon_High* is equal to 1 when the log of the de-trended EUA carbon future price is above its median. *Policies* is equal to 1 when an environmental policy is introduced, it is equal to -1 when an environmental policy is either weakened or rolled back, and it is equal to 0 otherwise.

[21] Diaz-Rainey et al. (2021) show that investors are pricing current policies when examining climate risk.

Table 11: EMC Return and Investor Climate Sentiment: Carbon price and policies

	(1)	(2)	(3)	(4)
Constant	-0.0141	0.0114	-0.0103	0.0091
	(0.0101)	(0.0154)	(0.0068)	(0.0150)
$\text{CSent}^{\perp}_{t-1}$	-0.3585^{**}		-0.2751^{**}	
	(0.1505)		(0.1229)	
carbon_High	0.0048	-0.0054		
	(0.0137)	(0.0113)		
$\text{CSent}^{\perp}_{t-1}\times$carbon_High	0.2593			
	(0.2439)			
Policies			-0.0036	-0.0052
			(0.0120)	(0.0115)
$\text{CSent}^{\perp}_{t-1}\times$Policies			0.0816	
			(0.2146)	
$\text{CSent}^{\perp}_{t-1}$ Q2		-0.0143		-0.0142
		(0.0210)		(0.0207)
$\text{CSent}^{\perp}_{t-1}$ Q3		-0.0336^{*}		-0.0343^{*}
		(0.0195)		(0.0205)
$\text{CSent}^{\perp}_{t-1}$ Q4		-0.0287		-0.0287
		(0.0198)		(0.0197)
$\text{CSent}^{\perp}_{t-1}$ Q5		-0.0826^{**}		-0.0588^{**}
		(0.0328)		(0.0266)
$\text{CSent}^{\perp}_{t-1}$ Q5$\times$carbon_High		0.0660^{**}		
		(0.0276)		
$\text{CSent}^{\perp}_{t-1}$ Q5$\times$Policies				0.0268
				(0.0312)
Obs.	117	117	117	117
Adj. R^2	0.0229	0.0395	0.0099	0.0085

Notes: The table reports the results of regressions of EMC on the interaction of lagged climate sentiment with a dummy variable to denote above median de-trended carbon price (*carbon_High*), and U.S. environmental policies (*Policies*). The variable *Policies* has a value of 1 if in that month the U.S. introduced an environmental policy, a value of -1 for either a rollback or weakening of environmental policies, and 0 otherwise. The sample is from February 2010 to October 2019 for EMC returns and from January 2010 to September 2019 for investor climate sentiment and the other variables. Newey and West (1987) standard errors are reported in parenthesis. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Note that changes to the EUA carbon futures price do not directly affect U.S. firms, however if investors revise their valuation of firms' climate risk, we expect the revisions would be more prominent when carbon prices are high. Specifically, when the carbon price is high, investors may demand higher returns to invest in emission stocks to be compensated for the higher risk. In Columns 1 and 2 of Table 11, we observe that the carbon price does not have a direct effect on EMC returns. Furthermore, EMC returns show a weaker reaction to investor climate sentiment when the carbon price is high. We do not find any difference in the reaction of EMC to climate sentiment when an environmental policy is introduced or rolled back in the U.S. (Columns 3 and 4).

5 Conclusions

In this paper, we propose to measure investor climate sentiment through sentiment analysis of StockTwits posts on climate issues. We find that when social interaction is low, investor climate sentiment tends to be more negative when there is an increase in concerns on the environmental impact of climate change and there are more news on the societal debate about climate change. The opposite is observed when social interaction is higher. Furthermore, investor climate sentiment tends to be more positive when there is an increase in the concerns on the business impact of climate change and new research on climate change is released as long as there is social interaction on the matter.

Our main empirical finding is that an increase in climate sentiment is associated with lower returns of the EMC portfolio. Given the relative high environmental impact and the subjective valuation of such information, emission stocks tend to be most sensitive to climate sentiment-based demand. At the same time, the subjective valuation of a firm's environmental impact increases the risk to arbitrage which may result in a relative mispricing of emission stocks. We find that the effect of investor climate sentiment on EMC returns eventually revert back to zero in the long-term. Furthermore, the reaction of EMC returns to investor climate sentiment is either positive or negative but weaker in months with salient but uninformative events such as a release of a report on climate change, high perceived climate change risk, abnormal weather events, and high carbon prices. Hence, these events help to correct the mispricing generated by irrational investors trading on climate sentiment.

We conclude that firms should disclose more and more accurate information on their exposure to climate risk as well as on their environmental impact to reduce information asymmetry and limits to arbitrage which will ultimately improve market efficiency.

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A StockTwits Data

In this section we provide more details on the data extracted from StockTwits. Specifically, we provide examples of posts containing strings that we decided to exclude from the list of search strings although correlated with the strings ‘climate change’, and ‘global warming’. We discuss the characteristics of StockTwits users, the tickers used in climate posts, and the changes made to the combined and augmented version of Jockers (2017) and Rinker’s augmented Hu and Liu (2004) positive/negative word list to adapt it to our context.

A.1 Posts Selection

We select StockTwits posts containing at least one of the following strings: ‘climate change’, ‘global warming’, ‘emission’, ‘pollution’, ‘extreme weather’, ‘extreme temperature’, and ‘environmental’.

Table 12: Examples of Posts with excluded search strings

Environment
“$SHY expecting 50% Fibonacci retracement to 83.38. Also: current 2 year note yield at 1.01% is still cheap in this **environment**”
“is anybody thinking buy $AA ahead of earnings in this bullish **environment** for materials & commodities? chart looking solid to me $$”
Energy
“$GBPUSD well S1 was not a price where rate demand runs out of upward **energy**. Perhaps MS1 @1.5793 will hold.”
“Inflation is low says Lacker despite large y/y rises in sugar, **energy**, milk, oj, hogs, copper, steel, health insurance increases, etc $FED”
Carbon
“Compare stock markets today to Nov 18 **.carbon** copy..if conts $DJIA sees 11920 in 2hrs and drop to 11770 b4 NY open tomorrow @Jim3917 $ #djia","cr”
“can’t tax **carbon** so let’s tax $GOOG! RT @Drudge_Report: Sarkozy proposes tax on GOOGLE...”
Temperature
“Our latest #economics insight: Why falling **temperatures** won’t mean rising natural gas prices”
“below normal **temperatures** expected in the northeast, hungry investors cannot wait to get their hands on natural gas stocks- $CHK reports wed”
Weather
“Pain in Spain or no, #Inditex keeps delivering. Sales up despite macros, **weather**; controlled markdown risk speak to strength of biz model $$”
“Don’t Blame the **Weather**: Record Low New Home Sales”

Notes: The table reports examples of posts with strings excluded from the set of search strings.

Although correlated with ‘climate change’, and ‘global warming’, we exclude the strings ‘environment’, ‘energy’, ‘carbon’, ‘temperature’, and ‘weather’ from the list of search strings because they are used in several contexts irrelevant for our analysis. In Table 12, we report several examples of posts containing the excluded strings. It can be seen that these posts are not relevant for the scope of our analysis and they would introduce noise in our sample if included.

A.2 StockTwits users characteristics

We collect a total of 43,445 climate posts exchanged on StockTwits from January 2010 to September 2019 by 12,364 unique users. StockTwits users can fill out user profiles with information on their level of experience (Novice, Intermediate, and Professional), investment approach (Fundamental, Technical, Momentum, Global Macro, Growth, and Value), and holding period (Day Trader, Swing Trader, Position Trader, and Long Term Trader). Table 13 presents the frequencies of user profile characteristics for users and messages posted about climate change. Around 65% of StockTwits users do not report their characteristics. Among the users that report their characteristics, about 24% classify themselves as professionals, 53% as intermediate, 23% as novice. Furthermore, professionals are more active on StockTwits than novices or intermediaries. Specifically, professionals post on average 6.02 climate messages per user against 2.63 and 3.60 posts per novices and intermediates, respectively. We expect investors with high level of experience to be more prone to report their characteristics. First, anecdotal evidence suggests that investors post on social networks to attract followers and gain fame or a job,[22] which makes it in the interest of professionals to declare their level of experience. Second, StockTwits users that do not report their level of experience post on average 3.26 climate messages per user which is in line with the level of activity of novices and intermediates. In our sample, the most common investment approach is technical, followed by growth and momentum. Furthermore, the most common holding period is swing trading followed by long term. These statistics are in line with Cookson et al. (2022) which analyse all StockTwits messages posted between January 2013 and June 2020.

[22]See the *Wall Street Journal* article “Retail Traders Wield Social media for Investing Fame” from April 21, 2015 on the fame motive for posting to investment social networks.

Table 13: Frequencies of User Profile Characteristics

	Number of Users	Percent of Users	Number of Climate Posts	Percent Climate Posts
Panel A: Experience				
Novice	987	7.98%	2,600	5.98%
Intermediate	2,330	18.85%	8,396	19.33%
Professional	1,058	8.56%	6,374	14.67%
None	7,989	64.62%	26,075	60.02%
Total	12,364	100%	43,445	100%
Panel B: Investment Approach				
Fundamental	687	5.56%	3,008	6.92%
Technical	1,359	10.99%	4,170	9.60%
Momentum	784	6.34%	2342.00	5.39%
Global Macro	162	1.31%	817	1.88%
Growth	854	6.91%	3,016	6.94%
Value	506	4.09%	3,302	7.60%
None	8,012	64.80%	26,790	61.66%
Total	12,364	100%	43,445	100%
Panel C: Holding Period				
Day Trader	616	4.98%	1,699	3.91%
Swing Trader	1,650	13.35%	4,725	10.88%
Position Trader	921	7.45%	3,758	8.65%
Long Term Investor	1,178	9.53%	6,840	15.74%
None	7,999	64.70%	26,423	60.82%
Total	12,364	100%	43,445	100%

Notes: The table reports summary statistics of user profile characteristics for users and messages posted about climate change. Panel A presents the frequency distribution of experience, Panel B presents the frequency distribution of investment philosophy, and Panel C presents the frequency distribution of holding period.

A.3 StockTwits 'cashtags'

The sample of climate posts mention 1,838 unique tickers, Figure 5 shows a word cloud of the tickers mentioned in our sample of climate posts. Table 14 focuses on the climate posts that mention a unique ticker as they can be directly linked to a particular stock. We report the 10 most frequent tickers, company name, industry, number of climate posts mentioning the ticker, and percentage of total climate posts mentioning the ticker. We can observe that most of the companies are involved in 'green' activities: production of electric vehicles (TSLA, KNDI), renewable chemicals and biofuels (GEVO, PLUG and BLDP), and pollution and treatment controls (CECE, ADES); while some are involved in 'brown' activities: mining (NAK), and oil related services (NES). The three most frequent tickers are $TSLA, $NAK, and $GEVO which represents respectively 4.65%, 3.47%, and 2.17% of all climate posts.

Table 14: 10 Most Frequent Tickers in Climate Posts

Ticker	Company name	Industry	Number Climate Posts	Percent Climate Posts
$TSLA	Tesla, Inc.	Auto Manufacturers	2022	4.65%
$NAK	Northern Dynasty Minerals Ltd.	Other Industrial Metals & Mining	1508	3.47%
$GEVO	Gevo, Inc.	Specialty Chemicals	942	2.17%
$KNDI	Kandi Technologies Group, Inc.	Auto Parts	799	1.84%
$CECE	CECO Environmental Corp.	Pollution & Treatment Controls	741	1.71%
$SPY	SPDR S&P 500 ETF	-	496	1.14%
$NES	Nuverra Environmental Solutions Inc.	Oil related services & Equipment	480	1.10%
$PLUG	Plug Power Inc.	Electrical Equipment & Parts	447	1.03%
$BLDP	Ballard Power Systems Inc.	Specialty Industrial Machinery	423	0.97%
$ADES	Advanced Emissions Solutions	Pollution & Treatment Controls	318	0.73%

Notes: The table reports the 10 most frequent tickers among the climate posts that mention a unique ticker. We report the ticker, company name, industry, number of climate posts mentioning the ticker, and percentage of total climate posts mentioning the ticker.

Figure 5: Word cloud of Tickers in StockTwits Climate Posts

Notes: The figure presents the word cloud of the tickers mentioned in StockTwits climate posts. Text size depends on the word frequency.

A.4 Sentiment Analysis

We use the R package sentimentr (Rinker, 2019) to perform sentiment analysis. The package is designed to calculate text polarity sentiment in an accurate and quick way. The advantage of the package is the use of 140 valence shifters, negators and amplifiers/deamplifiers, which respectively reverse, increase, and decrease the impact of a polarized word. The importance of valence shifters can be understood by looking at the examples in Table 15. In the table we confront the function sentiment() of the package sentimentr and the function get_sentiment() of the package syuzhet (Jockers, 2017). The main difference between the two packages is the use of valence shifters. In particular, the package syuzhet does not adopt any valence shifter, as such the function gives the same sentiment score

Table 15: Role of Valence Shifters in Sentiment Analysis

Sentence	sentiment (sentimentr)	get_sentiment (syuzhet)
I am happy	0.4330	0.7500
I am very happy	0.6750	0.7500
I am not happy	-0.3750	0.7500
I am not very happy	-0.0671	0.7500

Notes: The table presents the sentiment score of four sentences produced with the function sentiment of the R package sentimentr (Column 2), and the function get_sentiment of the R package syuzhet (Column 3).

to the four sentences as it only considers the presence or absence of positive/negative words. Being 'happy' a positive word, the syuzhet package gives a positive score of 0.750. Differently, the package sentimentr gives a score of 0.433 to the sentence 'I am happy', however if the amplifier 'very' is present the score rise to 0.675. Conversely, if the negator 'not' is used the sentiment score becomes negative.

We utilize the combined and augmented version of Jockers (2017) and Rinker's augmented Hu and Liu (2004) positive/negative word list as sentiment lookup values. Since the polarity score is dependent upon the polarity dictionary used, we adapt the dictionary to our context.

We dropped from the dictionary the following words (the sign in brackets identify the polarity sign attributed by the lexicon R package): boom (-), booming (-), bull (-), bullish (-), corporation (-), cut (-), cuts (-), demand (-), demanded (-), demands (-), director (+), economic (-), fight (-), fighting (-), fuels (+), global (+), gore (-), government (-), greater (+), greatest (+), intended (-), legal (+), like (+), lowest (-), management (+), nuclear (-), partner (+), pollution (+), pretty (+), share (+), shares (+), trump (-), white (+), would be (-), would have (-). Moreover, we added the following words (the sign in brackets identify the polarity sign we attributed to the term): arse (-), bearish (-), boom (+), booming (+), broken heart (-), bull (+), bull shit (-), bullish (+), bullsht (-), bullsh (-), department of environmental protection (neutral), dmn (-), embarrassed (-), environmental protection agency (neutral), fk (-), i like (+), lol (+), natural gas (neutral), not enough (-), sceptic (-), sceptically (-), scepticism (-), sceptics (-), sht (-), smiley (+), straight face (-), supreme court (neutral), tears of happiness (+), they like (+), vice president (neutral), we like (+), wink (+), you like (+).

In addition to this, we add to the list of valence shifters the amplifiers: pretty, higher, highest, highly, greater, and greatest; and the deamplifiers: low, lower, lowest, less.

A detailed description of the equation used by the algorithm in the R command sentiment() to assign value to polarity of each sentence can be found in Rinker (2019).

B Industry classification

Table 16: Summary of Industry Information

ICB Code	Industry Name	IPCC Code	IPCC Industry Name
Energy			
60101000	Integrated Oil & Gas	1A1bc	Other Energy Industries
60101010	Oil: Crude Producers	1B2	Flaring and fugitive emissions from oil and Natural Gas
60101015	Offshore Drill. & Other Serv.	1B2	Flaring and fugitive emissions from oil and Natural Gas
60101020	Oil Refining & Marketing	1B2	Flaring and fugitive emissions from oil and Natural Gas
60101030	Oil Equipment & Services	1A1bc	Other Energy Industries
60101040	Coal	1A2f4	Mining and quarrying
65101015	Conventional Electricity	1A1a	Power and Heat Generation
65102020	Gas Distribution	1A3e, 1B2	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
Transport			
40501010	Airlines	1A3a, 1C1	Domestic air transport, International aviation
50206010	Trucking	1A3b	Road transport (includes evaporation) (fossil)
50206020	Railroads	1A3c	Rail transport
50206030	Marine Transportation	1A3d, 1C2	Inland shipping (fossil), International navigation
50206060	Transportation Services	1A2f2, 1A3b	Transport equipment, Road transport (includes evaporation) (fossil)
Buildings			
40202010	Home Construction	1A4b	Residential (fossil)
50101035	Building Materials: Other	1A4a, 2A1	Commercial and public services (fossil), Cement production
50101010	Construction	1A2f6	Construction
Industry			
10102010	Semiconductors	2F7a	Semiconductor Manufacture
40101020	Automobiles	1A2f2	Transport equipment
45102020	Food Products	1A2e	Food and tobacco
45103010	Tobacco	1A2e	Food and tobacco
50202010	Electrical Components	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
50202020	Electronic Equip.: Control & Filter	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
50202025	Electronic Equip.: Gauges & Meters	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
50204000	Machinery: Industrial	1A2f3	Machinery
50206015	Commercial Vehicles & parts	1A2f2	Transport equipment
55101015	Paper	1A2d	Pulp and paper

(continued)

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ICB Code	Industry Name	IPCC Code	IPCC Industry Name
55102000	General Mining	1A2f4	Mining and quarrying
55102010	Iron & Steel	1A2a	Iron and steel
55102035	Aluminum	1A2b, 2C3	Non-ferrous metals, Aluminum production (primary)
55102050	Nonferrous Metals	1A2b	Non-ferrous metals
55103025	Gold Mining	1A2f4	Mining and quarrying
55103030	Plat.& Precious Metal	2Cr	Non-ferrous metals production
55201000	Chemicals: Diversified	1A2c	Chemicals
55201010	Chemicals and Synthetic Fibers	1A2c	Chemicals
55201015	Fertilizers	1A2c	Chemicals
55201020	Specialty Chemicals	1A2c	Chemicals
65102000	Multi-utilities	1A1a, 1A2f	Power and Heat Generation, Other industries (stationary) (fossil)
65103035	Waste & Disposal Svs.	6A	Solid waste disposal on land
AFOLU			
45102010	Farming, Fishing, Ranching & Plantations	1A4c3, 4A, 4B, 4C, 4Dr	Fishing (fossil), Enteric Fermentation, Manure management, Rice cultivation, Agricultural soils (direct)

C Timeline of events and U.S. environmental policies

Table 17: Timeline

Date	Event	Event type
01/01/2010	Stronger smog standard	Policies (+)
01/10/2010	Nation's First Greenhouse Gas Fuel Efficiency Standards for Trucks and Buses	Policies (+)
01/11/2010	Greenhouse gas reporting	Policies (+)
01/12/2010	UN Climate Change Conference	Conferences
01/12/2010	EPA Establishes Landmark Chesapeake Bay 'Pollution Diet'	Policies (+)
01/05/2011	Next Generation of Fuel Economy Labels Unveiled	Policies (+)
01/07/2011	Cross-State Air Pollution Rule	Policies (+)
01/08/2011	Fuel Efficiency and Greenhouse Gas Pollution Standards for Heavy-Duty Vehicles	Policies (+)
01/12/2011	UN Climate Change Conference	Conferences
01/12/2011	First National Standards for Mercury Pollution from Power Plants	Policies (+)
01/03/2012	EPA Proposes First Carbon Pollution Standard for New Power Plants	Policies (+)
01/04/2012	EPA Updates Air Pollution Standards for Oil and Natural Gas	Policies (+)
01/08/2012	Obama Administration Finalizes Historic 54.5 mpg Fuel Efficiency Standards	Policies (+)
01/12/2012	UN Climate Change Conference	Conferences
01/12/2012	EPA Strengthens Air Standards for Fine Particles, Reducing Harmful Soot Pollution	Policies (+)
01/06/2013	Comprehensive Plan for Climate Change	Policies (+)
01/09/2013	IPCC Report "AR5 Climate Change 2013: The Physical Science Basis"	Reports
01/11/2013	UN Climate Change Conference	Conferences
01/03/2014	IPCC Report "AR5 Climate Change 2014: Impacts, Adaptation, and Vulnerability"	Reports
01/04/2014	New Rules for Cleaner Fuels and Cars	Policies (+)
01/04/2014	IPCC Report "AR5 Climate Change 2014: Mitigation of Climate Change"	Reports
01/05/2014	Third U.S. National Climate Assessment report	Reports
01/06/2014	First Guidelines Proposed to Cut Carbon Pollution from Existing Power Plants	Policies (+)
01/09/2014	UN Climate Summit	Conferences
01/10/2014	IPCC Report "AR5 Synthesis Report: Climate Change 2014"	Reports
01/11/2014	US-China Agreement on Climate Change	Policies (+)
01/12/2014	UN Climate Change Conference	Conferences
01/12/2014	First National Regulations for Coal Ash	Policies (+)
01/02/2015	Keystone XL veto	Policies (+)
01/09/2015	EPA issues notice of violation to Volkswagen	Policies (+)
01/11/2015	President Obama rejected TransCanada's Keystone XL Pipeline Proposal	Policies (+)
01/12/2015	UN Climate Change Conference and Paris Agreement	Conferences
01/04/2016	Paris Climate Accord	Policies (+)
01/06/2016	President Obama Signs Lautenberg Chemical Safety for the 21st Century Act	Policies (+)
01/11/2016	UN Climate Change Conference	Conferences
01/03/2017	Trump signed a presidential permit to allow TransCanada to build the Keystone XL pipeline	Policies (-)
01/05/2017	14 states signed a petition urging the President Trump to stay in the Paris Agreement	Policies (+)
01/06/2017	U.S. Withdraws from the Paris Climate Accord	Policies (-)
01/10/2017	EPA Proposes Repeal of the Clean Power Plan	Policies (-)
01/10/2017	Fourth National Climate Assessment Report	Reports
01/11/2017	UN Climate Change Conference	Conferences
01/01/2018	EPA loosens regulations on toxic air pollution	Policies (-)
01/04/2018	EPA starts rollback of car emissions standard	Policies (-)
01/07/2018	Trump officials propose rollbacks of endangered species act rules	Policies (-)
01/08/2018	Trump announces plan to weaken Obama-era fuel economy rules	Policies (-)

(continued)

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Date	Event	Event type
01/09/2018	EPA repeals Obama-era methane rules	Policies (-)
01/10/2018	President Trump signs bill to clean up ocean plastics	Policies (+)
01/10/2018	IPCC Special Report "Global Warming of 1.5°C"	Reports
01/11/2018	2nd volume of Fourth National Climate Assessment Report	Reports
01/12/2018	Trump administration rolls back Obama-era coal rules	Policies (-)
01/12/2018	UN Climate Change Conference	Conferences
01/04/2019	Trump signs pipeline orders	Policies (-)
01/05/2019	Offshore drilling safety rules rolled back	Policies (-)
01/09/2019	UN Climate Action Summit	Conferences