Investors' Climate Sentiment and Financial Markets[*][†]

Caterina Santi[‡]

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Abstract

We propose a measure of investors' climate sentiment by performing sentiment analysis on StockTwits posts on climate change and global warming. We find that investors' climate sentiment generates a mispricing in the Emission-minus-Clean (EMC) portfolio (Choi et al., 2020), the portfolio that invests in emission stocks and goes short on clean stocks. Specifically, when investors share a positive attitude towards climate change, they tend to overvalue the negative externalities produced by emission stocks. Moreover, we show that carbon prices are a successful incentive to reduce CO_2 emissions. Finally, a portfolio strategy that uses information on investors' climate sentiment and carbon prices generates a return of 9.77% annually.

Keywords: Climate Sentiment, Asset Pricing, Social Networks, StockTwits.
JEL classification: C58; G13; G18; Q54.

1 Introduction

Climate change is the biggest challenge of our times. Policy-makers are increasingly concerned about the impact of climate risks on economic growth and financial stability. The financial system may play a prominent role in achieving the global climate targets by promoting more sustainable investments. Pástor et al. (2020) shows that sustainable investing produces positive social impact by lowering firms emissions and by shifting real investment toward low-emission firms. However, institutional and retail investors are still not fully pricing climate risks and opportunities in their portfolios (Faccini et al., 2021; Alok et al., 2020; Krueger et al., 2020; Benedetti et al., 2019; Hong et al., 2019), thus exposing economies and society to new sources of financial instability.

This paper contributes to the Behavioural Finance literature on the impact of investors' sentiment on asset pricing (Siganos et al., 2017; Kaplanski et al., 2015; Mian and Sankaraguruswamy, 2012; Schmeling, 2009; Baker and Wurgler, 2007; De Long et al., 1990). In particular, we focus on the effect of investors' climate sentiment on the pricing of emission (carbon-intensive) and clean (low-emission) stocks. When sentiment about climate change becomes more positive, investors

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[‡]Department of Accounting and Finance, University College Cork – caterina.santi@ucc.ie

may update their own valuation of firms. They may believe that carbon-intensive firms' will have lower cashflows in the future because of either climate change, higher costs of future emissions or tighter environmental regulations. Indeed, investors may update their beliefs about the level of environmental social norms in the economy and anticipate future developments of climate regulation (Hsu et al., 2020). Moreover, socially responsible investors may avoid carbon-intensive stocks and increase their investments on low-emission stocks.

Recently, Dunz et al. (2018) has developed the EIRIN Stock-Flow Consistent behavioural model to assess how investors could react to the impact of stochastic climate-led disasters, as well as to the introduction of a carbon tax and green subsidies to address climate risks, accounting for their expectations on climate risks. They find that investors' climate sentiment could be crucial in influencing portfolios' reallocation toward green assets, thus amplifying climate policies' impacts. Song et al. (2019) find that the impact of the fossil energy market, especially crude oil, on the renewable energy stock market is greater than the impact of investor sentiment on the renewable energy stock market. Furthermore, investor sentiment towards renewable energy can explain the return and volatility of renewable energy stock to a certain degree. Differently, Reboredo and Ugolini (2018) have shown that Twitter sentiment is not substantial in shaping prices and trading for renewable energy companies.

We propose to use StockTwits (`https://stocktwits.com/`) posts related to climate change from January 1, 2010 to September 30, 2019 to build a measure of investors' climate sentiment. StockTwits is a financial platform where investors can exchange trading ideas and other stock-related information. Similar to Twitter, messages are of a small size (maximum 140 characters) and consist of ideas, links, charts and other data. Already in August 2010, Time Magazine inserted StockTwits in the list of Top 50 Websites of 2010. Today, StockTwits has a total monthly audience of about 1.5 million users. The platform attracts young professionals, with 60% of its users under 44. Microblogging forums have acquired popularity in the last few years, more and more investors use these online platforms to share information about the market and individual stocks. Thus, the community of users of microblogging forums is potentially more representative of all investors. Furthermore, microblogging data is readily available at low cost permitting a faster and less expensive creation of indicators than traditional sources, and can also contain new information that is not present in historical quantitative financial data. Another advantage of microblogging data is that users post very frequently, reacting to events in real-time and allowing a real-time assessment that can be exploited during the trading day. Since 2014, Thomson Reuters has developed a measure of the sentiment surrounding any listed company by taking feeds from both Twitter and StockTwits. Although StockTwits data have already been used in a number of context to measure disagreement, sentiment and attention (Cookson and Niessner, 2020; Agrawal et al., 2018; Li et al., 2016; Oliveira et al., 2013; Oh and Sheng, 2011), they have not been used to measure investors sentiment on climate change and global warming. Several works have proposed the use of Twitter to measure climate sentiment (Loureiro and Alló, 2020; Dahal et al., 2019; Cody et al., 2015), however the link between climate sentiment and financial markets has not been explored yet.

Concerning climate sentiment, Loureiro and Alló (2020) analyse Twitter messages related to climate change in the UK and Spain. They find that messages in the UK related to climate change are less negative than in Spain. However, the two countries show quite similar views about preferences for energy policies. Dahal et al. (2019) shows that the overall discussion on Twitter about climate change is negative, especially when users are reacting to political or extreme weather events. Moreover, the discussion of climate change in the US is less focused on policy-related topics

than other countries. Cody et al. (2015) measure sentiment on tweets containing the word "climate" collected between September 2008 and July 2014. The authors document that natural disasters, climate bills, and oil-drilling can contribute to a decrease in happiness while climate rallies, a book release, and a green ideas contest can contribute to an increase in happiness. Furthermore, they show that Twitter is a valuable resource for the spread of climate change awareness. Indeed, their analysis suggests that responses to climate change news are predominately from climate change activists rather than climate change deniers.

The paper employs data for the US from January 1, 2010 to September 30, 2019. Financial data are retrieved from Thomson Reuters Datastream. We propose to build a measure of investors' climate sentiment by performing sentiment analysis on StockTwits posts related to climate change and global warming. Then, we explore the relationship among the Emission-minus-Clean portfolio (EMC) (Choi et al., 2020), carbon prices, oil prices, performance of the market portfolio and investors' climate sentiment. The EMC portfolio invests in a value-weighted portfolio of emission (carbon-intensive) stocks and it goes short on a value-weighted portfolio of clean (low-emission) stocks. Similarly to Choi et al. (2020), we identify a stock as an emission (carbon-intensive) stock if it belongs to 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 (low-emission) stocks. Since emission stocks have a higher exposure to carbon risk than clean stocks, we include the settlement price of the Carbon Emission Allowances (EUA) futures in the analysis. Moreover, given the documented relationship between oil prices, carbon prices and carbon emissions (Zou, 2018; Hammoudeh et al., 2014), we consider also the Crude Oil WTI spot price. We also include the overall performance of the financial market by including the price of the S&P 500. The paper accounts also for the possible effect of some exogenous variables. Specifically, we consider: US abnormal temperatures, US abnormal extreme weather events, US abnormal damages caused by extreme weather events, international environmental disasters, international events such as the UN summits on climate change and the global climate strike, and US environmental policies. Previous research has explored how extreme temperatures are affecting the intensity of Google search and interaction on Twitter on "climate change" and "global warming" (Sisco et al., 2017; Yeo et al., 2017; Lineman et al., 2015; Herrnstadt and Muehlegger, 2014; Lang, 2014). Recently, Choi et al. (2020) have found that people revise their beliefs about climate change upwards when experiencing abnormal temperatures. Moreover, retail investors sell stocks of carbon-intensive firms in such weather conditions. Furthermore, natural disasters, environmental policies, oil-drilling, and international events on climate change can contribute to a decrease or increase in climate sentiment (Cody et al., 2015).

Turning to our main contributions, this work proposes a measure of investors' climate sentiment by performing sentiment analysis on the StockTwits posts on climate change and global warming. Being StockTwits content exclusively about investing, we argue that it is a less noisy data set which allows us to better address the study of the effects of climate sentiment on financial markets than other social networks such as Twitter.[1]

Second, we show that an increase in investors' climate sentiment causes an increase in the price of the EMC portfolio. Specifically, we observe that when investors have a positive attitude towards climate change (higher climate sentiment) they tend to undervalue emission stocks and to overvalue clean stocks, hence an increase in optimism may fuel the mispricing of the EMC portfolio

[1] Data on investors' climate sentiment and social interaction from January 2010 to September 2019 are available from the author's website, https://www.caterinasanti.com/research

which may lead to short term positive returns. Moreover, we find that investors' climate sentiment causes an increase in carbon prices. The more the investors are aware of the challenges presented by climate change and global warming the more the carbon price increases which should deter firms from rising CO_2 emissions.

Our results also add to the literature on the public effort to put a price on greenhouse gas emissions by issuing tradable emission permits or through a carbon tax. Given that public support for carbon taxes is generally low, only few countries have implemented them. Moreover, there is only limited evidence on their causal effect on the level of emissions (Andersson, 2019; Sterner, 2015; Baranzini and Carattini, 2014). Differently, tradable emission permits although more popular, they bring other issues concerning their pricing and the fact that they reduce firms incentives to invest in abatement technologies or capital than a constant emissions tax (Zhao, 2003). This paper finds that an increase in the carbon price causes a reduction in the value of the EMC portfolio. This implies that investors lower their expectations on future cashflows generated by carbon-intensive firms because they expect higher costs of future emissions.

We next examine the long-term relationship among the EMC portfolio, carbon prices, oil prices, market performance and investors' climate sentiment. We document that the five variables share a long-term relationship. However, only investors' climate sentiment adjusts to disequilibrium. Additionally on average, investors' climate sentiment is higher either when an international environmental disasters occurs or there is an international event related to climate change. These findings suggest that natural disasters caused by climate change and global warming as well as international events such as the global climate strikes may reduce skepticism on the matter and increase awareness. Another interesting result is that carbon prices are lower on average when an environmental policy is introduced, while they are higher when an environmental policy is either weakened or rolled back. This implies that the market can play a role in reducing carbon emissions and hence achieving global climate targets. Indeed, when policy-makers opt for a weakening of environmental policies, carbon prices tend to be higher in order to deter an increase in carbon emissions.

We provide two additional pieces of evidence on the relationship among the five variables in our analysis. First, we find that the EMC portfolio responds only to shocks on carbon prices and investors' climate sentiment. Specifically, the variation in EMC lasts for about two months. A positive shock to carbon prices generate a temporary reduction in the value of the EMC portfolio. Differently, a boost in investors' optimism on climate change temporarily increases the value of EMC. Second, the variance decomposition analysis shows that the EMC price have substantial influence on oil prices, market portfolio and investors' climate sentiment. Furthermore, climate sentiment marginally influence EMC price and oil prices.

Finally, we use our findings to inform the construction of profitable portfolio strategies. Although investment in the EMC portfolio generates null returns, we find that timing the investment in and out of the EMC portfolio according to information on investors' climate sentiment and carbon prices produces significantly positive returns. Specifically, the portfolio strategy gains 9.77% annually.

Our results have important implications on the role of the financial system to achieve global climate targets. Investors' climate sentiment affects the pricing of emission and clean stocks. As such, investors behaviour could amplify climate policies' impacts. Specifically, when investors have a higher awareness and a more positive attitude towards climate change and global warming they may allocate their resources in favour of clean stocks rather than emission stocks. Furthermore,

investors may expect that emission stocks will have lower cashflows in the future because of the losses generated by climate change, higher costs of future emissions and tighter environmental regulations. This work sheds also light on the role of carbon prices. First, we document that carbon prices are effective in deterring firms from increasing CO_2 emissions. Indeed, an increase in carbon prices cause a reduction in the value of the EMC portfolio. Second, an increase in investors' climate sentiment pushes carbon prices up.

We argue that policy-makers should promote initiatives to increase public awareness on climate change, and they should raise the price of CO_2 and other greenhouse-gas emissions. Furthermore, firms should disclose information on their climate risk and level of carbon emissions to reduce information asymmetries hence improving market efficiency. Bolstad et al. (2020) report that today 60% of publicly traded firms reveal at least something about climate change, however 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.

2 Investors Climate Sentiment

We use the posts exchanged on StockTwits to measure investors' climate sentiment. StockTwits was founded in 2008 as a social networking platform for investors to share their opinions about stocks. Participants can post messages of up to 140 characters and exchange ideas, links, charts and other data. StockTwits provided us with data on the universe of messages posted between January 1, 2010 and September 30, 2019. Among all the posts exchanged on StockTwits, we selected those containing at least one of the following 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. 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 and thus it is important for us to account for both terms (Whitmarsh, 2009). Moreover, the two terms are perceived differently. Politicization of scientific words as a means of directing public awareness caused climate change to be perceived as being more positive than global warming (Lineman et al., 2015).

By looking at the posts containing the strings "climate change" and "global warming", we realized that these search strings were correlated with other words such as, "emission", "pollution", "weather", "temperature", "environment", "carbon" and "energy". However, when we used the above search strings one-by-one we realized that the words "weather", "temperature" and "environment" were often used to talk about topics not related to climate change and global warming. In order to avoid introducing noise in our sample, 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". We decided to not use "energy" and "carbon" as search strings since they were capturing numerous posts not related to climate issues. 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 included posts not discussing climate issues. For example, we verified that the search word emission was capturing posts containing the string "remission" relative to cancer. Hence, we eliminated all the posts with the string "remission" unless they were including another of the above search strings. We repeated the procedure several times

in order to eliminate irrelevant posts from our sample. We end up with 43,445 climate posts exchanged on StockTwits from January 2010 to September 2019, with an average of 370 posts per month, and 14 per day.

Figure 1: Word cloud of StockTwits Posts on Climate issues

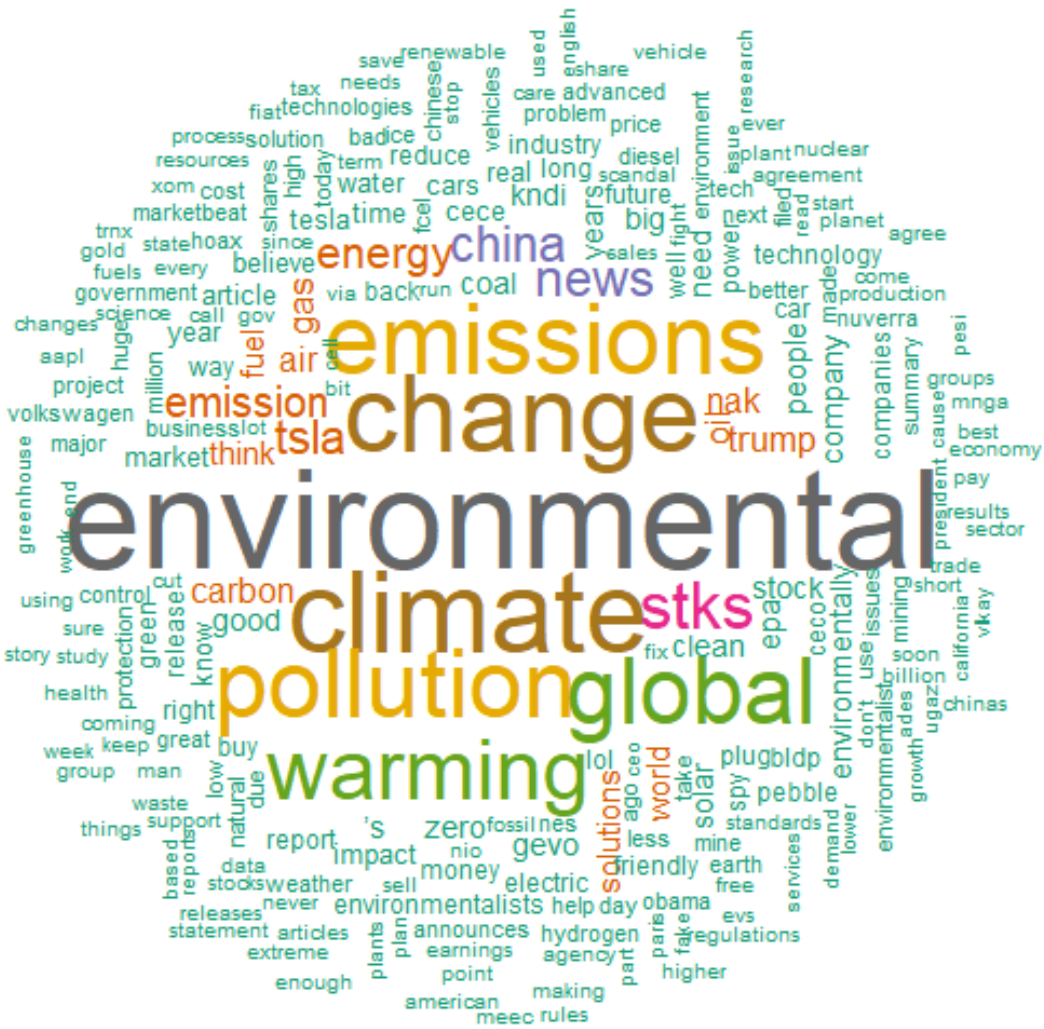

Figure 1 shows a word cloud of the StockTwits posts on climate issues, the words have different sizes according to their frequency in the posts (how often they are mentioned in the text). It is interesting to observe that among the words not included in the search strings, the most frequent is the term “news” with a frequency of 3290. This highlights the critical role of media in influencing discussion and attention on climate issues. The word “china” has a frequency of 2920 and it mainly appears in the posts either as a negative example in terms of pollution and environmental regulation or in relation to the manufacturing facilities in Shanghai of “tsla” (frequency 2706).[2] The word “energy” (frequency 2522) appears in relation to climate issues in the discussion on energy

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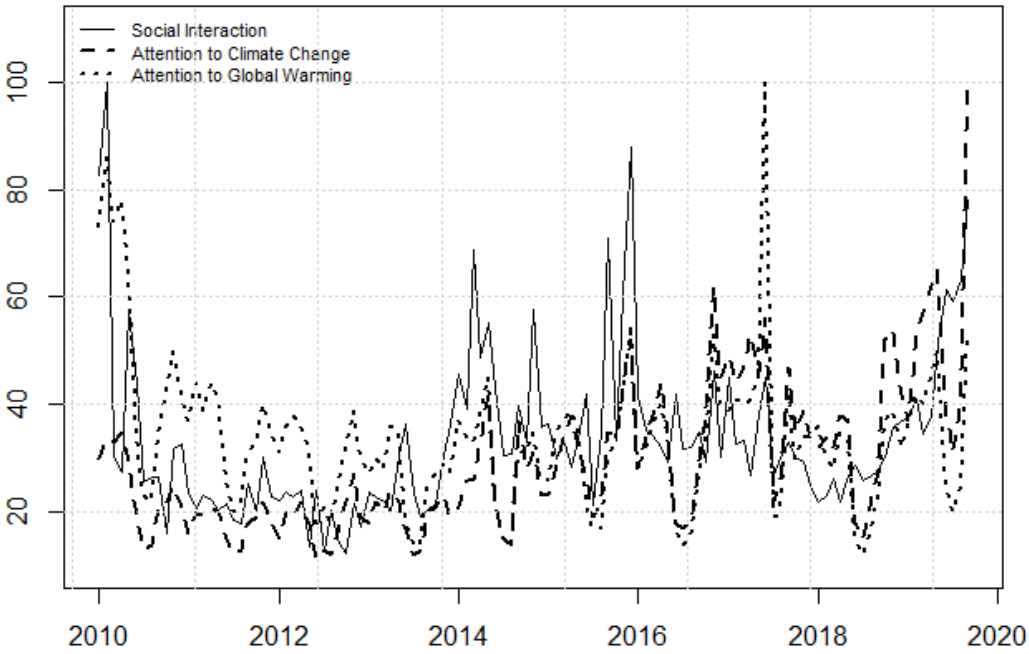
[2] TSLA is the symbol for Tesla, the well-known American company specialized in electric vehicle manufacturing, battery energy storage from home to grid scale and, through its acquisition of SolarCity, solar panel and solar roof tile manufacturing.

consumption and green energies. Not surprisingly the word "trump" has a frequency of 1882. US President Donald Trump contradictory and confusing position on climate change has been in the spotlight in several occasions. The company "nak" (frequency 1687), NYSE symbol of Northern Dinasty Minerals Ltd., generated a lot of discussion among environmentalists and climate change deniers on the environmental approval of its mining activities in Alaska. Other words related to fossil fuels such as "oil", and "gas", and the words "carbon", and "fuel" have an overall frequency of more than 5500. Finally, a positive word that appears frequently is "solutions" (frequency 1495).

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



Before introducing the computation of investors' climate sentiment from StockTwits posts on climate change, we want to validate the use of the platform StockTwits to measure climate sentiment. Indeed, someone may argue that investors do not discuss about climate related issues in platforms like StockTwits. To do so, we build a variable of social interaction on climate issues and we compare it with the Google Search Volume Index of the topics "climate change" and "global warming".

The use of Google Search Volume Index (SVI) as a measure of investors attention has been pioneered by Da et al. (2011) which documents that an increase in SVI predicts higher stock prices in the next two weeks and an eventual price reversal within the year. Recently, several other papers have studied Google SVI for climate change and global warming and relate it to local weather conditions (Choi et al., 2020; Cavanagh et al., 2014; Herrnstadt and Muehlegger, 2014; Lang, 2014; Kahn and Kotchen, 2011). Given that Google SVI is widely adopted in the literature,

we compare social interaction on climate change in StockTwits with the Google searches on climate change and global warming.

The variable social interaction is built using the monthly ratio of the number of posts on climate related issues with the total number of posts exchanged on StockTwits. Similarly to the Google Search Volume Index, 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. For example, a value of social interaction equal to 50 implies that in that month there were half of social interaction than the month with the highest level of social interaction.

We use SVI provided by Google Trends to measure attention to climate change and global warming. Our time span goes from January 2010 to September 2019, we use both topics "climate change" and "global warming". It is important that we use topics instead of search terms as this account for varying languages and spelling errors as Google's algorithms can group different searches that have the same meaning under a single topic.

Figure 2 shows the time series of social interaction and attention to climate change and global warming. As we can observe, the series are highly correlated. The highest level of social interaction on climate issues is recorded in February 2010 together with a high attention on global warming, in that month anomalous temperatures were reported. Specifically, cold air in the wake of several reinforcing Arctic air masses dominated much of the US during February, creating temperatures that were much-below average in the Deep South and below average in the Plains and Mid-Atlantic States. Meanwhile, upper-level patterns contributed to warmer-than-average temperatures in the Northwest and Northeast climate regions (NOAA, 2010). Another peak in social interaction is registered in March 2014, differently from the previous one this peak does not come together with an increase in attention to climate change and global warming. To boost discussion on StockTwits in March 2014 was the statement by Tim Cook, chief executive of Apple, 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. In November 2014, China and the US surprised pretty much everyone by announcing that they would work together to tackle the climate crisis. Instead, Volkswagen emissions scandal was at the center of the discussion in September 2015 when social interaction reached another peak. Few months later, the Conference of the Parties (COP 21) to the United Nations Framework Convention on Climate Change (UNFCCC) was hosted in Paris from 30 November to 12 December. The conference concluded with a new global agreement on climate change known as the Paris Agreement which led to a renewed attention and interaction on climate issues. Unfortunately, in June 2017 President Trump announced the US withdrawal from the Paris agreement as it was considered not beneficial for the US economy. In the same day a bipartisan coalition of states and unincorporated self-governing territories formed the US Climate Alliance which committed to upholding the objectives of the 2015 Paris Agreement on climate change within their borders. These events boosted attention on climate change and global warming, and a slight increase in the interaction on the topic in StockTwits. From mid-2018, both attention on climate change and global warming, and social interaction started to increase thanks to, among other things, the action of the climate activist Greta Thunberg with a peak in September 2019 when the Global Climate Strike took place.

Given these observations, we argue that StockTwits can be used to measure investors' climate sentiment. Moreover, differently from other platforms such as Twitter, StockTwits is only about investing which make it a better source of data to study the effect of climate sentiment on financial markets.

2.1 Computation of the Sentiment Score

We develop a measure of investors' climate sentiment by performing textual analysis on the StockTwits posts on climate change and global warming. Data on investors' climate sentiment and social interaction from January 2010 to September 2019 are available from the author's website.[3] Sentiment analysis is an increasing area of research and application, due to the sheer size of unstructured data that is now available (Gandomi and Haider, 2015; Feldman et al., 2007). Numerous textbooks have been published that illustrate the major algorithms to be used for text mining, and specifically for sentiment analysis (Cambria et al., 2017; Liu, 2015; Feldman et al., 2007). In this paper, we use the R package sentimentr (Rinker, 2019). The package has already been used in a number of contexts: to predict stock prices from Google news (Chen et al., 2015); to analyze sentiments expressed on Twitter by energy consumers (Ikoro et al., 2018); and to analyze the sentiment of patients with critical illness (Weissman et al., 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.

Table 1: 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 three sentence produced with the function sentiment of the R package sentimentr (column 2), and the function get_sentiment of the R package syuzhet (column 3).

The importance of valence shifters can be understood by looking at the examples in Table 1. 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 to the four sentences as it only consider 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, transforming the sentence in "I am not happy", the sentiment score becomes negative and equal to -0.375. Instead the sentence "I am not very happy" receives a negative but higher sentiment score of -0.067.

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.[4] Also, we replace emoticons with their word equivalent through the replace_emoticon() command, so as to be included in the score computation.

An interesting observation is the correlation of the climate sentiment score with attention and social interaction on climate change and global warming (see Table 14). Climate sentiment is positively correlated with attention to climate change (0.4152) and negatively correlated with attention to global warming (-0.1505). This evidence is consistent with Lineman et al. (2015) and

[3]The web page is https://www.caterinasanti.com/research

[4]More details can be found in Appendix C

Whitmarsh (2009) which argue that "climate change" is shown in a more positive light than "global warming". Also, the messaging guru Frank Luntz suggested to President George W. Bush to swap out the term "global warming" and replace it with "climate change," which Luntz thought sounded less threatening. Moreover, the correlation coefficient between social interaction and attention to climate change is 0.5060, while correlation with attention to global warming is 0.4347. We consider this as a validation of our measure of social interaction, indeed we expect that a higher public attention to climate issues can trigger interaction on these topics also among investors.

Table 2: Correlation matrix

	Attention to Climate Change	Attention to Global Warming	Social Interaction	Climate Sentiment
Attention to Climate Change	1.0000			
Attention to Global Warming	0.4005	1.0000		
Social Interaction	0.5060	0.4347	1.0000	
Climate Sentiment	0.4152	-0.1505	0.3040	1.0000

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), Social Interaction (share of StockTwits climate related posts), and Climate Sentiment (sentiment score of StockTwits climate related posts).

3 Data Description

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

3.1 Financial Markets Information

We employ Thomson Reuters Datastream for financial data. We consider stocks traded in the two major US financial markets, the New York Stock Exchange and Nasdaq. Since DataStream may suffer from data errors, we winsorize raw returns at the top and bottom 2.5% in each exchange in each month. As in 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. Doing so, we end up with a total of 4,663 stocks.[5]

The Intergovernmental Panel on Climate Change (IPCC), the leading international body for the assessment of climate change, identifies five major industry sectors as major emission sources: Energy; Transport; Buildings; Industry (such as chemicals and metals); 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 Thomson Reuters Datastream with the IPCC category codes.[6] 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. Our dataset is composed of 3,732 clean stocks (average market capitalization $7,741 millions) and 931 emission stocks (average market capitalization $8,691 millions). Similarly to Choi et al. (2020), we compute the price of the portfolio Emission-minus-Clean (EMC). The EMC portfolio goes long on a value-weighted portfolio of emission stocks and it goes short on a value-weighted portfolio of clean stocks, hence its price is given by the difference of the price of the emission portfolios which includes stocks in carbon-intensive industries, and the price of

[5]From the series of returns we build the series of prices, for example the log price in January 2010 is given by the sum of the log price in December 2009 and the log return in January 2010 and so on.

[6]Appendix A contains a list of Industry Classification Benchmark (ICB) codes available from Thomson Reuters Datastream and the matching IPCC category codes which are classified as carbon intensive.

the clean portfolio which includes stocks in industries with low emissions. Alternative ways to identify emission and clean stocks consist in using firm-level environmental performance scores constructed by the ESG ("Environmental, Social, and Governance") data providers such as MSCI and Sustainalytics. However, this data cover only a subset of firms and they should be interpreted with caution.[7] Throughout the paper, we use the IPCC definitions because they are available for all firms moreover industries are a popular investment style.

A carbon price should encourage polluters to reduce the amount of carbon dioxide they emit into the atmosphere, this can take the form of either a carbon tax or a requirement to purchase permits to emit. In this work we use the log of the settlement price of the ICE-ECX Carbon Emission Allowances (EUA) futures (*carbon*). The 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.

Burning of fossil fuels including oil is contributing to the warming of our planet and to climate change. Moreover, oil prices depends on carbon prices and carbon emissions (Zou, 2018; Hammoudeh et al., 2014). For these reasons, we decide to include oil price in our analysis. In particular, we employ the log of the Crude Oil WTI spot price (*oil*). We also control for the overall performance of the financial markets by using the log price of the S&P 500 as the price of the market portfolio (Mkt).

3.2 Severe Weather Events and Temperatures

We obtain monthly temperature data from the US Climate Divisional Database, which have data from January 1895 to July 2020 (https://www.ncdc.noaa.gov/cag/national/time-series/110/tavg/all/1/1895-2020?base_prd=true&begbaseyear=2010&endbaseyear=2020).

Since recent climate research is increasingly confident in linking climate change to more frequent and severe natural disasters (National Academies of Sciences, Engineering, and Medicine and others, 2016), we consider also the frequency and the damages caused by extreme weather events in the US. We obtain data for severe weather events in the US from the Severe Weather Data Inventory (SWDI) (https://www.ncdc.noaa.gov/ncdcs-severe-weather-data-inventory). The records in SWDI come from a variety of sources in the National Climatic Data Center (NCDC) archive.[8]

We conjecture that either abnormal temperatures or an abnormal frequency and damages of severe weather events may affect investors' climate sentiment. Hence, following Choi et al. (2020), we decompose the US temperature, frequency and damages of extreme weather events into a predictable, seasonal, and abnormal component. In particular, first we compute the average temperature for the US in a given month t ($Temp_t$). Second, we compute the average monthly temperature over the 120 months prior to t ($AvgTemp_t$). Third, we compute $MonTemp_t$, the difference between the average temperature in the same calendar month in the previous 10 years minus $AvgTemp_t$. The series of abnormal temperatures ($AbTemp_t$) is computed in the following

[7] The methodology used to compute the ESG scores is not disclosed with the data, and ESG ratings produced by different data providers are often not consistent (Friede, 2019; Avetisyan and Hockerts, 2017; Semenova and Hassel, 2015).

[8] 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.

way (Choi et al., 2020):

$$AbTemp_t = Temp_t - AvgTemp_t - MonTemp_t, \tag{1}$$

We follow a similar procedure to compute the series of abnormal frequency of extreme weather events ($AbEWE_t$):

$$AbEWE_t = EWE_t - AvgEWE_t - MonEWE_t. \tag{2}$$

where EWE_t is the number of extreme weather events in a given month t, $AvgEWE_t$ is the average number of monthly extreme weather events over the 120 months prior to t, and $MonEWE_t$ is the difference between the average number of extreme weather events in the same calendar month in the previous 10 years minus $AvgEWE_t$.

Finally, the abnormal damages caused by severe weather events ($AbDamages_t$) is computed as follows:

$$AbDamages_t = Damages_t - AvgDamages_t - MonDamages_t, \tag{3}$$

where $Damages_t$ is the total damages caused by severe weather events in the US in a given month t; $AvgDamages_t$ is the average $Damages_t$ over the 120 months prior to t; $MonDamages_t$ is the difference between the average damages in the same calendar month in the previous 10 years minus $AvgDamages_t$. Since we need 10 years of data prior to January 2010 to compute the series of abnormal temperature and abnormal weather events, we retrieve data from January 2000 to September 2019.

3.3 International Events on Climate Change and US Environmental Policies

We build two dichotomous variables for international environmental disasters ($Disasters$), such as the damage to the nuclear reactor in Japan in March 2011; and international events ($International$) such as the UN summits on climate change, signature of the Paris agreement, and the global climate strikes. A recent research by Ramelli et al. (2020) shows that the unanticipated success of the first Global Climate Strike on March 15, 2019 has caused a substantial stock price reaction on high-carbon intensity companies in Europe.

We also build a categorical variable for US environmental policies ($Policies$). The variable $Policies$ has a value of 1 if in that month the US introduced an environmental policy such as the US 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 US environmental policies is retrieved from the Environment Protection Agency (EPA) website (EPA, 2019), and two National Geographic articles (National Geographic Staff, 2020, 2019).[9]

4 Empirical Analysis

This work wants to explore the relationship among the Emission-minus-Clean (EMC) portfolio, carbon price ($carbon$), oil price (oil), performance of the market portfolio (Mkt) and investors' climate sentiment ($Sent$). We also consider some exogenous variables that may influence our

[9] A full list of events is available in Appendix B

set of endogenous variables, that is US abnormal temperatures ($AbTemp$), US abnormal extreme weather events ($AbEWE$), US abnormal damages caused by extreme weather events ($AbDamages$), international environmental disasters ($Disasters$), international events ($International$) such as the UN summits on climate change and the global climate strikes, and US environmental policies ($Policies$).

Well established econometric models to study the relationships among a set of financial variables in a nonstructural way include the vector autoregressive model (VAR) and vector error correction model (VECM). The VAR model is a generalization of the univariate autoregressive model to multivariate time series. Each equation of the VAR uses as its explanatory variables lags of all the variables and likely a deterministic trend and seasonal dummies.

$$VAR(p): \; X_t = A_1 X_{t-1} + ... + A_p X_{t-p} + BE_t + w_t, \tag{4}$$

where p is the maximum number of lags included in the VAR, X_t is a vector of endogenous variables at time t, E is a vector of exogenous variables at time t, and w_t is a vector of errors. Sims (1980) introduces VAR model into economic field and promotes the widespread application in dynamic analysis of economic system. VAR models should be applied to stationary series. If the series in levels are non-stationary, first differences to original series are one possible solution.

$$VAR(p): \; \Delta X_t = A_1 \Delta X_{t-1} + ... + A_p \Delta X_{t-p} + B\Delta E_t + \Delta w_t, \tag{5}$$

where ΔX_t is a vector of the endogenous variables in first-difference, similarly ΔE_t is a vector of the exogenous variables in first-difference. However, differencing the series may ignore possibly important long-run relationships between the levels. An alternative solution consists in testing whether the levels regressions are cointegrated. If two or more series are individually integrated, suppose they are first-order integrated I(1), and some linear combination of them has a lower order of integration, I(0), then the series are said to be cointegrated. The usual approach is to use Johansen's method for testing whether or not cointegration exists. As long as there is a cointegration relationship between variables, the error correction model can be derived from the autoregressive distributed lag model. The advantage of VECM over VAR is that the resulting VAR from VECM representation has more efficient coefficient estimates.

$$VECM(p-1): \; \Delta X_t = AX_{t-1} + \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{p-1} \Delta X_{t+1-p} + BE_t + w_t, \tag{6}$$

where $A = -(I - A_1 - ... - A_p)$, and $\Gamma_i = -A_{i+1}$ from the VAR(p) model. The matrix A can be written as $A = \alpha\beta'$ where α is a vector of adjustment coefficients, and β is a vector of the cointegration coefficients which represents the long-term relationship among the endogenous variables.

4.1 Summary Statistics

In this section we present some summary statistics of the main variables employed in the analysis.

Figure 3 shows the time series plot of the price of the EMC portfolio, the carbon, oil, and market price, and the sentiment score of the StockTwits posts on climate issues.

The value-weighted EMC portfolio follows an increasing trend. It is interesting to observe from Table 3 that EMC is strongly positively correlated with climate sentiment (0.6340), and the performance of the market portfolio (0.8324). Differently, EMC is negatively correlated with

carbon price (-0.0245), WTI oil price (-0.1899), abnormal temperatures (-0.1003), and abnormal frequency of extreme weather events (-0.1409). The price of EMC is always positive, this means that carbon-intensive stocks have a higher value than low-emission stocks.

Figure 3: Main Variables

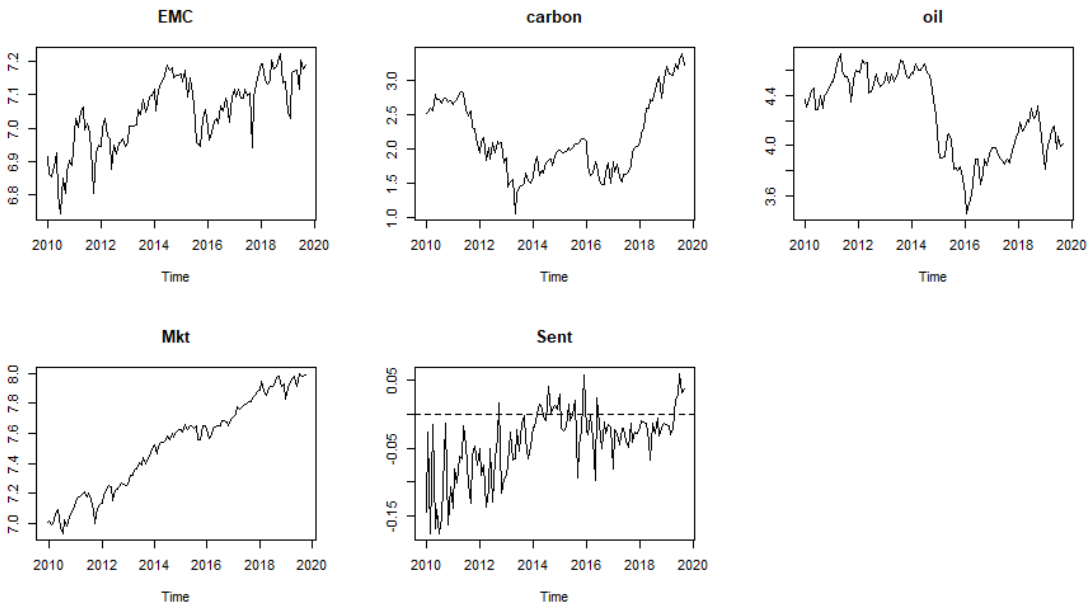


Table 3: Correlation matrix

	EMC	carbon	oil	Mkt	Sent	AbTemp	AbEWE	AbDamages
EMC	1.0000							
carbon	-0.0245	1.0000						
oil	-0.1899	0.0104	1.0000					
Mkt	0.8324	0.0526	-0.5974	1.0000				
Sent	0.6340	-0.0860	-0.3129	0.6454	1.0000			
AbTemp	-0.1003	-0.1367	-0.2278	-0.0149	-0.0103	1.0000		
AbEWE	-0.1409	0.3419	0.2942	-0.2752	-0.2229	-0.1549	1.0000	
AbDamages	0.0119	-0.0707	-0.1130	0.1007	0.0079	-0.1399	-0.0028	1.0000

Notes: The table reports the correlation matrix of EMC (log price of the value-weighted Emission-minus-Clean portfolio), *carbon* (log settlement price of the ICE-ECX EUA futures), *oil* (log price of WTI oil), Mkt (log price of the S&P 500), $Sent$ (sentiment score of StockTwits climate related posts), $AbTemp$ (abnormal temperatures), $AbEWE$ (abnormal extreme weather events), and $AbDamages$ (abnormal damages from extreme weather events).

The carbon price should deter polluters from emitting greenhouse gases. Hence, higher the carbon price, higher the incentive. Carbon price reached its lowest level of 1.054 in May 2013, after that it followed an increasing trend. Only in mid-2016 it collapsed by 18% in four months and it kept oscillating around the value of 1.50 for almost one year to start increasing again from mid-2017. Correlation analysis shows that carbon prices tend to increase with abnormally low temperatures (-0.1367, Table 3) and an increase in the frequency of abnormal extreme weather events (0.3419, Table 3).

WTI oil price follows generally an increasing trend. However, from mid-2014 to the end of the year, WTI oil collapsed by 50%, crushing marginal forms of energy production, ranging from shale oil and tar sands to renewable like solar. Oil prices started to increase again from April 2015. In August 2015, world stock markets went down substantially with interlinked drops in commodities such as oil. From Table 3, we observe that oil prices are negatively correlated with the market

performance (-0.5974), investors' climate sentiment (-0.3129), abnormal temperatures (-0.2278), and abnormal damages caused by extreme weather events (-0.1130). Oil prices are positively correlated only with abnormal extreme weather events (0.2942).

The price of the market portfolio (S&P 500) follows an upward trend. It registers a down peak in September 2011 because of the debt crisis in Europe. In August 2015, world stock markets were down substantially, wiping out all gains made in 2015, with interlinked drops in commodities such as oil, which hit a six-year price low, copper, and most of Asian currencies, but the Japanese yen, losing value against the US dollar. The S&P 500 index peaked at 2,930 on 20th September 2018 close and dropped 19.73% to 2,351 by Christmas Eve.

Table 4: Summary Statistics

	Mean	Median	St.Dev.	Skewness	Kurtosis	ADF test in level	ADF test in first diff.
EMC	7.0461	7.0537	0.1060	-0.4916	-0.4752	0.1712	< 0.0100
carbon	2.1553	2.0162	0.5385	0.4646	-0.8542	0.9620	< 0.0100
oil	4.2446	4.3028	0.3223	-0.3275	-1.1253	0.6513	< 0.0100
Mkt	7.5175	7.5736	0.3103	-0.1774	-1.2242	0.3418	< 0.0100
Sent	-0.0406	-0.0273	0.0502	-0.7879	0.2967	0.2041	< 0.0100
AbTemp	0.3252	0.2870	2.1384	0.3470	0.7375	0.0734	< 0.0100
AbEWE	165.3983	-38.3000	1407.8061	1.1611	3.6164	0.0554	< 0.0100
AbDamages (million)	131.9730	-259.1565	6253.0650	5.0154	33.4864	< 0.0100	< 0.0100

Notes: The table reports the Mean, Median, Standard deviation, Skewness, Excess Kurtosis and the p-value of the Augmented Dickey Fuller unit root test of the main variable of interest. EMC is the log price of the value-weighted Emission-minus-Clean portfolio. *carbon* is the log settlement price of the ICE-ECX EUA futures. *oil* is the log price of WTI oil. Mkt is the log price of the S&P 500. $Sent$ is the climate sentiment score measured on StockTwits climate related posts. $AbTemp$ is abnormal temperatures. $AbEXE$ measures abnormal extreme weather events. $AbDamages$ measures abnormal damages from extreme weather events.

The sentiment score is negative for almost the entire period with only few exceptions. This evidence is consistent with Dahal et al. (2019) which use Twitter to measure climate sentiment. They document that the overall discussion is negative, especially when users are reacting to political or extreme weather events. In 2014, several episodes boosted investors' climate sentiment. Given the negative correlation of sentiment with oil prices (-0.3129, Table 3), the aforementioned collapse in oil price from July 2014 to March 2015 contributed to a positive investors' climate sentiment. Further, at the UN Climate Summit on September 23rd 2014, dozens of Governments, businesses, civil society and indigenous peoples pledged to halve deforestation by 2020 and to end within the following decade. Also, in September 2014 hundreds of thousands of people across 150 countries took part in protests dubbed the People's Climate March - flagged as the biggest ever call-to-action on climate change. On November 12th 2014 China and the US made a joint announcement on climate change which boosted optimism. In 2015, only three months register a positive climate sentiment score. In May 2015, Pope Francis addressed climate change in his encyclical, *Laudato si*. Given the Pope's international influence, this progressive encyclical contributed to raising global awareness about climate change and inspiring people to live more sustainable lives. In August 2015 a drop in stock markets was interlinked with a drop in oil. December 2015 was distinguished by the signature of the Paris agreement. The agreement presents an action plan to limit global warming 'well below' 2°C. In 2019 the climate sentiment score starts an upward trend, becoming positive from May until the end of the series. In those months, the initiatives of the climate activist Greta Thunberg become more and more popular attracting the attention of the media and shaping the public attitudes towards climate change and global warming.

Table 4 reports the Mean, Median, Standard deviation, Skewness, Excess Kurtosis and the p-values of the Augmented Dickey Fuller (ADF) unit root test of the time series in levels and in first difference. We observe that abnormal temperatures, abnormal frequency and damages of extreme

weather events have a positive mean, this highlights that temperatures tend to be abnormally higher than in the past in the US and extreme weather events are more frequent and they are causing more damages. The ADF tests the null hypothesis that a unit root is present in a time series sample. We observe that all the series in levels have a unit root at the 5% confidence level (except *AbDamages*), while their first differences are stationary.

4.2 VAR Analysis

The first issue of the VAR model is to determine the number of lags for endogenous variables. The larger the number of lags for endogenous variables is, the more it can entirely reflect the dynamic nature of the model. However, higher orders requires more parameters to estimate. This is a trade-off in the selection of the proper order to estimate the VAR. There are several methods that can determine optimal lag order for the VAR model. In this work we consider up to five lags and we adopt the Akaike Information criterion (AIC), the Hannan–Quinn information criterion (HQ), the Schwarz information criterion (SC), and the forecasting prediction error (FPE) (see Table 5). The VAR model includes the following endogenous variables: Emission-minus-Clean (EMC), carbon, oil, Mkt, Sent; and the following exogenous variables: AbTemp, AbEWE, AbDamages, Disasters, International, Policies, and seasonal dummies. According to Panel A of Table 5, the AIC and FPE suggest two lags for the VAR model in levels, while HQ and SC suggest to include only one lag. We decide to consider two lags to better investigate the dynamic nature of the model, hence the VECM model in Section 4.4 will include one lag. Instead in Panel B, all methods suggest one as the optimal lag of the VAR model in first-difference.

Table 5: Lag Selection VAR

Lags	1	2	3	4	5
Panel A: Variables in levels					
AIC(n)	-28.2529	**-28.3383**	-28.0418	-27.8700	-27.8972
HQ(n)	**-27.1203**	-26.9596	-26.4168	-25.9988	-25.7799
SC(n)	**-25.4615**	-24.9402	-24.0368	-23.2582	-22.6787
FPE(n)	0.0055e-10	**0.0052e-10**	0.0073e-10	0.0091e-10	0.0094e-10
Panel B: Variables in first-difference					
AIC(n)	**-27.8308**	-27.7636	-27.6432	-27.6143	-27.5342
HQ(n)	**-26.6921**	-26.3773	-26.0092	-25.7328	-25.4052
SC(n)	**-25.0237**	-24.3462	-23.6155	-22.9763	-22.2860
FPE(n)	**0.0084e-10**	0.0093e-10	0.0108e-10	0.0117e-10	0.0136e-10

Notes: The table reports the Akaike Information criterion (AIC), the Hannan–Quinn information criterion (HQ), the Schwarz information criterion (SC), and the forecasting prediction error (FPE) of the VAR model with endogenous variables: VW, carbon, oil, Mkt, Sent; and exogenous variables: AbTemp, AbEWE, AbDamages, Disasters, International, Policies, and seasonal dummies for up to 5 lags. Panel A reports the results for the VAR model in levels, Panel B reports the results for the VAR model in first-difference.

Since the model's endogenous variables are integrated of order one, we decide to estimate the VAR model in first difference. Once we determine the optimal lag, we proceed at estimating the VAR(1) model. Results are reported in Table 6.

We find that the price of the EMC portfolio is negatively auto correlated, and that an increase in carbon prices reduces the value of the EMC portfolio. This evidence shows that carbon prices work well as a deterrent to emit carbon-dioxide. This finding is likely driven by an update of investors' beliefs about the cost of future emissions. Differently, an increase in investors' climate sentiment is associated with an increase in the EMC portfolio's value. A more positive attitude towards climate change by investors (higher investors' climate sentiment) may induce them to undervalue emission stocks and to overvalue clean stocks, this means that the EMC portfolio is mispriced and

specifically its price is below its true value. Hence, adjustments of the EMC portfolio towards its true value generates an increase in value which we document in Table 6. Furthermore, the results show that the carbon price is influenced by the level of investors' climate sentiment. In particular, a more optimistic sentiment boosts an increase in carbon prices. The oil price is positively auto correlated and it is negatively associated with the market performance. The market portfolio is negatively auto correlated, moreover it depends positively on the oil price and investors' climate sentiment and it is negatively associated with the carbon price. Climate sentiment is negatively auto correlated. Moreover, climate sentiment is positively associated with oil prices. When oil prices increases, investors move towards other sources of energies less reliant on fossil fuels and they tend to be more positive in the discussion on climate change. We do not observe any effect of US environmental policies on investors' climate sentiment. This evidence is also documented by Dahal et al. (2019), which, using messages exchanged on Twitter, find that the discussion of climate change in the US is less focused on policy-related topics than other countries. Differently from Choi et al. (2020), we do not find any effect of abnormal temperatures and abnormal extreme weather events on our endogenous variables. This may be due to the fact that our analysis is conducted at a national level, while Choi et al. (2020) study the effect of local weather events on the performance of local stocks. We also do not observe any effect of international environmental events and US environmental policies on our variables.

We perform the Jarque Bera normality test on the VAR residuals, and we find that only the residuals of the carbon regression are not normally distributed at 5% confidence level. Moreover, VAR residuals do not show any serial dependence and heteroskedasticity (see Table 7).

Table 6: VAR Estimates

	ΔEMC_t	$\Delta carbon_t$	Δoil_t	ΔMkt_t	$\Delta Sent_t$
ΔEMC_{t-1}	-0.3004^{*}	0.5075	0.2610	0.0687	0.0187
	(0.1523)	(0.4609)	(0.2810)	(0.1188)	(0.1321)
$\Delta carbon_{t-1}$	-0.0635^{*}	-0.1501	0.0022	-0.0486^{*}	0.0063
	(0.0342)	(0.1034)	(0.0631)	(0.0267)	(0.0296)
Δoil_{t-1}	0.0576	-0.1715	0.2467^{*}	0.0913^{*}	0.1022^{*}
	(0.0693)	(0.2098)	(0.1279)	(0.0541)	(0.0601)
ΔMkt_{t-1}	0.1723	-0.2559	-0.7889^{**}	-0.3419^{**}	-0.1381
	(0.1909)	(0.5777)	(0.3522)	(0.1489)	(0.1656)
$\Delta Sent_{t-1}$	0.2108^{**}	0.6216^{**}	0.0879	0.1572^{*}	-0.4625^{***}
	(0.1018)	(0.3080)	(0.1878)	(0.0794)	(0.0883)
Constant	0.0027	0.0058	0.0038	0.0119^{***}	0.0026
	(0.0049)	(0.0148)	(0.0090)	(0.0038)	(0.0043)
$\Delta AbTemp_t$	0.0012	-0.0027	-0.0011	-0.0003	-0.0006
	(0.0021)	(0.0065)	(0.0040)	(0.0017)	(0.0019)
$\Delta AbEWE_t$	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\Delta AbDamages_t$	0.0000	-0.0000	0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\Delta Disasters_t$	0.0055	-0.0082	0.0326	0.0138	0.0214
	(0.0167)	(0.0506)	(0.0308)	(0.0130)	(0.0145)
$\Delta International_t$	0.0118	0.0407	0.0085	0.0085	0.0066
	(0.0117)	(0.0353)	(0.0215)	(0.0091)	(0.0101)
$\Delta Policies_t$	0.0034	-0.0285	0.0106	0.0048	0.0013
	(0.0077)	(0.0232)	(0.0141)	(0.0060)	(0.0066)
R^2	0.2271	0.1830	0.1871	0.2512	0.3550
Adj. R^2	0.0423	-0.0124	-0.0073	0.0721	0.2008
Num. obs.	115	115	115	115	115
Normal Residuals	YES	NO	YES	YES	YES
AIC	-1565.5040				
Sum of Squared Residuals	3.4187				
Log Likelihood	897.7520				

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table reports the estimates of the VAR(1) model with endogenous variables in first difference: EMC, carbon, oil, Mkt, Sent; and exogenous variables in first difference: AbTemp, AbEWE, AbDamages, Disasters, International, Policies, and seasonal dummies. We omit seasonal dummies coefficients from the table.

Table 7: Tests on VAR Residuals

Test	Chi-sq	df	p-value
Adjusted Portmanteau	381.6489	375.0000	0.3952
ARCH	1106.5212	1125.0000	0.6472

Notes: The table reports three multivariate normality tests of the VAR residuals: the Adjusted Portmanteau- and Breusch-Godfrey test for serially correlated errors (row 1), and the ARCH-LM test (row 2).

4.3 Causal Analysis

We perform the Granger causality test on the variables in first-difference. The Granger causality test is conducted to determine whether one time series is useful in forecasting another. A time series X is said to Granger-cause Y if it can be shown that lagged values of X can provide statistically significant information about future values of Y. Rows 1 to 5 of Table 8 show the p-values of the bivariate Granger causality test. Variables in the columns are the causal variables, variables in the rows are the dependent variables.

Table 8: Granger Causality Test

	Causal Variables				
Dependent Variables	ΔEMC	$\Delta carbon$	Δoil	ΔMkt	$\Delta Sent$
ΔEMC	-	0.0350	0.3150	0.2872	0.0211
$\Delta carbon$	0.8576	-	0.8916	0.9101	0.0252
Δoil	0.3811	0.8525	-	0.0525	0.5716
ΔMkt	0.3846	0.0531	0.1219	-	0.0810
$\Delta Sent$	0.6838	0.6312	0.0844	0.8925	-
All	0.7716	0.1604	0.1701	0.0070	0.0420

Notes: The table reports the p-values of the Granger causality test. Variables in the columns are the causal variables, variables in the rows are dependent variables. We use variables in first difference to perform the Granger Causality. The multivariate Granger causality analysis (last row) is performed by fitting a VAR(1) to the time series in first difference with endogenous variables: EMC, carbon, oil, Mkt, Sent; and exogenous variables: AbTemp, AbEWE, AbDamages, Disasters, International, Policies, and seasonal dummies.

We find that the carbon price Granger-causes the price of the EMC portfolio (5% confidence level), and the market price (10% confidence level). Investors' climate sentiment Granger-causes the price of the EMC portfolio (5% confidence level), the carbon price (5% confidence level), and the market price (10% confidence level). Furthermore, oil price Granger-causes climate sentiment (10% confidence level). The last row of Table 8 reports the p-values of the multivariate Granger causality test. The multivariate Granger causality test is performed by fitting a VAR(1) to the time series in first difference with endogenous variables: EMC, carbon, oil, Mkt, Sent; and exogenous variables: AbTemp, AbEWE, AbDamages, Disasters, International, Policies, and seasonal dummies. We observe that the behaviour of the market Granger-causes EMC, carbon price, oil price and climate sentiment at 5% confidence level. Moreover, investors' climate sentiment Granger-causes EMC, carbon price, oil price and market price at 5% confidence level.

To sum up, we find that an increase in the carbon price generates a reduction in the value of the EMC portfolio. Differently, an increase in investors' climate sentiment causes an increase in the price of the EMC portfolio. Since a wide literature has documented that investors have a limited attention, we believe that when investors have a positive attitude towards climate change (higher climate sentiment) they tend to undervalue emission stocks and to overvalue clean stocks, hence an increase in optimism may fuel the mispricing of the EMC portfolio which may lead to short term positive returns. We also observe that investors' climate sentiment causes an increase in carbon prices. The more the investors are aware of the challenges presented by climate change

and global warming the more the carbon price increases which should deter firms from rising CO_2 emissions. Oil prices depends strongly on the performance of the market as a whole. Another interesting result is that an increase in carbon prices cause a reduction of market performance, while an increase of investors' climate sentiment causes an increase in market performance.

4.4 VECM Analysis

Given that estimating the VAR in first-difference may overlook any long-run relationship between the variables, in this section we explore whether our variables are cointegrated. Cointegration relationship between variables in the VAR model is generally tested with the Johansen (1988) and Johansen and Juselius (1990) method.

Johansen cointegration test on the EMC portfolio price, carbon prices, oil prices, market prices and investors' climate sentiment (see Table 9) shows that, both trace and maximum eigenvalue tests suggest to accept the null hypothesis, under the 5% level, that one positive cointegrating relationship exists. This means there is a stable and long-run equilibrium relationship among the variables. Given the existence of a cointegration relationship, a VECM can be estimated.

Table 9: Unrestricted Cointegration Rank Test

Rank	Trace test			Eigenvalue test	
	Statistic	p-value	Adj. p-value	Statistic	p-value
0	116.8432	< 0.001	< 0.001	54.6256	<0.001
1	62.2176	0.06636	0.08586	29.4332	0.1024
2	32.7844	0.35276	0.38073	22.9652	0.1148
3	9.8192	0.92557	0.92991	6.8144	0.9022
4	3.0048	0.86502	0.86722	3.0048	0.8666

Notes: The table reports the results of the Trace and Maximum Eigenvalue test for cointegration rank. Column 4 reports the adjusted p-value for small sample size of the Trace test.

Cointegration analysis demonstrates that EMC portfolio price, carbon prices, oil prices, market prices and investors' climate sentiment do have a long-run equilibrium relationship, however, in the short term, the five variables may be in disequilibrium. The short-term imbalance and dynamic structure can be expressed as a VECM of order one (since Table 5 shows that the optimal lag order of VAR in level is two, VECM's lag order should be one).

Below we report the equation for the error correction term (ECT):

$$\begin{aligned} ECT_t =& EMC_t - 0.0169 \times carbon_t - 0.1026 \times oil_t - 0.6557 \times Mkt_t \\ & - 1.4654 \times Sent_t - 1.9531 + 0.0042t. \end{aligned} \tag{7}$$

Note that we include both a constant and a trend component in the cointegrating equation. Indeed, from Figure 3 we observe that several variables in our model show a linear deterministic trend. Hence, we conjecture that our variables are sharing both a stochastic and a deterministic trend. In this case, a deterministic trend should be included in the specification of the error correction term to eliminate it. From the equation of ECT, it can be seen that in the long-run, other things equal, each percentage-point increase in carbon prices will cause the increase of 0.0169 percentage points in EMC, each percentage-point increase in oil prices will cause the increase of 0.1026 percentage points in EMC, each percentage-point increase in market prices will cause the increase of 0.6557 percentage points in EMC, and each percentage-point increase in investors' climate sentiment will cause the increase of 1.4654 percentage points in EMC.

We plot the cointegration equation in Figure 4 to verify its stationarity. From visual inspection

of the series we can argue that ECT is stationary and it oscillates around its average of zero. We also perform the ADF test on ECT which confirms its stationarity at 5% confidence level.

Figure 4: Error Correction Term

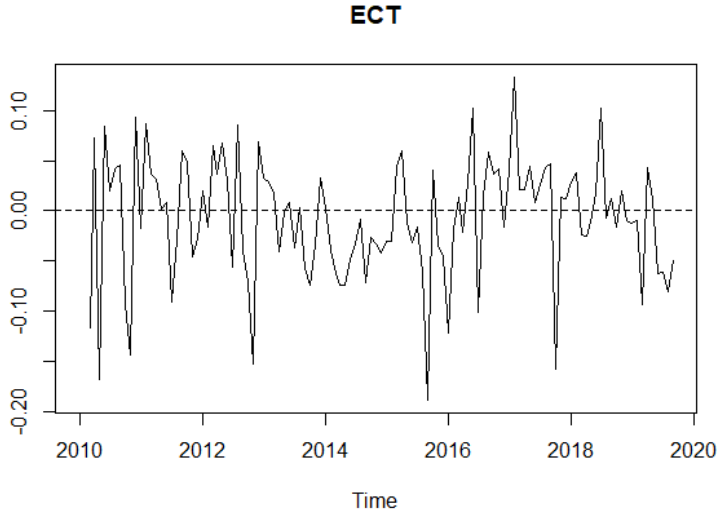


Table 10: VECM Results

	ΔEMC	$\Delta carbon$	Δoil	ΔMkt	$\Delta Sent$
ECT	-0.1557	0.2293	0.3702	0.0548	0.4917^{***}
	(0.1253)	(0.3733)	(0.2304)	(0.0997)	(0.0962)
ΔEMC_{t-1}	-0.2275	0.2831	0.0995	0.0338	-0.1776
	(0.1545)	(0.4605)	(0.2842)	(0.1230)	(0.1187)
$\Delta carbon_{t-1}$	-0.0678^{**}	-0.2038^{**}	0.0119	-0.0497^{*}	0.0128
	(0.0328)	(0.0976)	(0.0602)	(0.0261)	(0.0252)
Δoil_{t-1}	0.0582	-0.2032	0.1984	0.0662	0.0288
	(0.0677)	(0.2019)	(0.1246)	(0.0539)	(0.0520)
ΔMkt_{t-1}	0.1132	-0.0243	-0.6349^{*}	-0.2864^{*}	0.0926
	(0.1937)	(0.5771)	(0.3561)	(0.1541)	(0.1487)
$\Delta Sent_{t-1}$	0.0700	0.7001^{*}	0.3518	0.1802	-0.1146
	(0.1370)	(0.4082)	(0.2519)	(0.1090)	(0.1052)
AbTemp	0.0003	-0.0073	-0.0019	-0.0004	-0.0026
	(0.0024)	(0.0072)	(0.0044)	(0.0019)	(0.0018)
AbEWE	0.0000	0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
AbDamages	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Disasters	0.0086	0.0535	0.0513	0.0201	0.0385^{**}
	(0.0239)	(0.0713)	(0.0440)	(0.0190)	(0.0184)
International	0.0225	0.0076	0.0174	0.0216^{*}	0.0229^{**}
	(0.0140)	(0.0416)	(0.0257)	(0.0111)	(0.0107)
Policies	-0.0019	-0.0807^{***}	0.0211	0.0057	0.0031
	(0.0098)	(0.0292)	(0.0180)	(0.0078)	(0.0075)
Num. obs.	115	115	115	115	115
Normal Residuals	YES	NO	YES	YES	YES
AIC	-3253.7490				
Sum of Squared Residuals	3.2451				
Log Likelihood	929.9848				

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table reports the estimates of the VECM model with one cointegrating relation ECT, endogenous variables: EMC, carbon, oil, Mkt, Sent; and exogenous variables: AbTemp, AbEWE, AbDamages, Disasters, International, Policies, and seasonal dummies. We omit seasonal dummies coefficients from the table.

Estimates of the VECM model are presented in Table 10. The coefficients of the error correction term (ECT) represents the adjustment coefficients to the long-run equilibrium. The adjustment coefficients show the extent to which any disequilibrium in the previous period affects any adjustment in the endogenous variables. We find that the adjustment coefficients are significant only

in the climate sentiment equation. Specifically, the previous year deviations of investors' climate sentiment from the long-run equilibrium are corrected at a speed of 49.17%. The results suggest that ceteris paribus, a percentage-point increase in carbon prices have an immediate (short-run) negative effect of -0.0678 percentage points in the EMC portfolio (5% confidence level), -0.2038 percentage points in carbon prices (5% confidence level), and -0.0497 percentage points in market performance (10% confidence level). Further, ceteris paribus a percentage-point increase in market performance have a short-run negative effect of -0.6349 percentage points in oil prices (10% confidence level) and -0.2864 percentage points in the market performance itself (10% confidence level). We also observe that, ceteris paribus a percentage-point increase in investors' climate sentiment have a short-run positive effect of 0.7001 percentage points in carbon prices (10% confidence level). Additionally on average, investors' climate sentiment is higher either when an international environmental disasters occurs or there is an international event related to climate change. These findings suggest that natural disasters caused by climate change and global warming as well as international events such as the global climate strikes may reduce skepticism on the matter and increase awareness. Another interesting result is the effect of US policies on carbon prices. Indeed, the negative coefficient of *Policies* implies that carbon prices are lower on average when an environmental policy is introduced, while they are higher when an environmental policy is either weakened or rolled back. This implies that the market can play a role in reducing carbon emissions and hence achieving global climate targets. Indeed, when policy-makers opt for a weakening of environmental policies, carbon prices increase in order to deter an increase in carbon emissions.

We perform the Jarque Bera normality test on the VECM residuals, and we find that only the residuals of the carbon regression are not normally distributed at 5% confidence level. Moreover, VECM residuals do not show any serial dependence and heteroskedasticity (see Table 11).

When we compare the overall performance of the VECM model with that of the VAR model in first-difference, we observe that the AIC and the sum of squared residuals are lower for the VECM model than the VAR, and the Log Likelihood is higher for the VECM than the VAR. We conclude that the VECM model describe better our data.

Table 11: Tests on VECM Residuals

Test	Chi-sq	df	p-value
Adjusted Portmanteau	351.6537	355.0000	0.5402
ARCH	1137.5351	1125.0000	0.3908

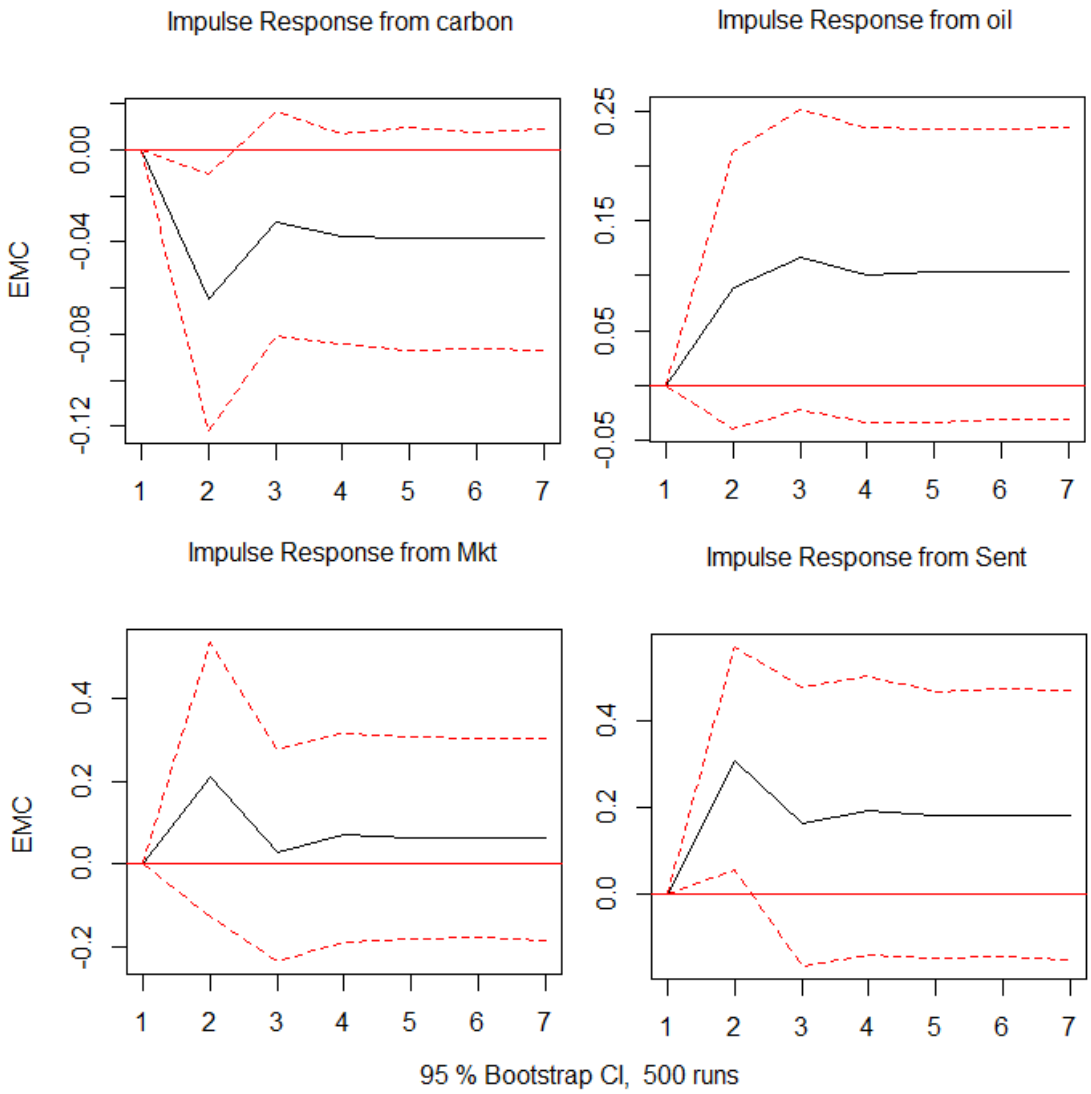
Notes: The table reports three multivariate normality tests of the VECM residuals: the Adjusted Portmanteau- and Breusch-Godfrey test for serially correlated errors (row 1), and the ARCH-LM test (row 2).

4.5 Impulse Response Function

In this section, we explore the effects of a shock on an endogenous variable on the performance of the EMC portfolio. In order to analyze dynamic effects of the model responding to certain shocks as well as how the effects are among the five variables, we conduct further analysis with impulse response function based on VECM. We consider up to 6 periods ahead.

Impulse response function is adopted to reflect shock effect of a system on an internal variable. According to the bivariate Granger test results, EMC is caused by carbon prices and investors' climate sentiment. Further, the VECM analysis shows a short term negative relationship between EMC and carbon prices, and that EMC does not adjust to disequilibrium in the long-term re-

Figure 5: EMC Response to Shocks



lationship expressed by the cointegrating equation. Figure 5 shows the EMC response to shocks on carbon prices, oil prices, market prices and investors' climate sentiment. Confidence intervals are computed with a bootstrap with 500 iterations and they represent 5% confidence level. We find that only shocks to carbon prices and climate sentiment lead to a variation in EMC that last for about two months. Specifically, a positive shock to carbon prices generate a temporary reduction in the value of the EMC portfolio. Differently, a boost in investors' optimism on climate change temporarily increases the value of EMC. We believe that when investors are optimistic about climate change they tend to undervalue emission stocks and to overvalue clean stocks, hence an increase in optimism fuel the mispricing of the EMC portfolio which lead to short term positive returns. Suppose that the emission portfolio has a true value of 100, however investors attribute to the emission portfolio a biased value of 80. Now consider a clean portfolio with a value of 80, if the investors are optimistic about climate change, they may attribute to the clean portfolio a higher value of 100. Hence, although the true value of the EMC portfolio is 20, it is sold on the

market at -20. Since investors are mispricing the EMC portfolio because of their positive attitude towards climate change, the price of the EMC portfolio will increase up to reach its true value of 20.

4.6 Portfolio Analysis

In this section, we use the results of the VAR and VECM analysis to inform the construction of portfolio strategies.

From the impulse response functions we have observed that shocks in investors' climate sentiment lead to an increase in the price of the EMC portfolio, while shocks in carbon prices lead to a decrease in the price of the EMC portfolio. We suggest the construction of portfolios that use such information. In particular, we build a portfolio SentEMC which suggests to invest in the EMC portfolio when changes in climate sentiment are positive and to sell the EMC portfolio otherwise. Indeed when investors' climate sentiment increases we expect to observe an increase in the price of the EMC portfolio in the next month and vice versa.

$$Ret_t^{SentEMC} = \begin{cases} Ret_t^{EMC} & \text{if } \Delta Sent_{t-1} \geq 0 \\ -Ret_t^{EMC} & \text{if } \Delta Sent_{t-1} < 0. \end{cases} \quad (8)$$

We construct also another portfolio exploiting the information in carbon prices. The portfolio CarbEMC suggests to invest in the EMC portfolio when changes in carbon prices are negative and to sell the EMC portfolio otherwise.

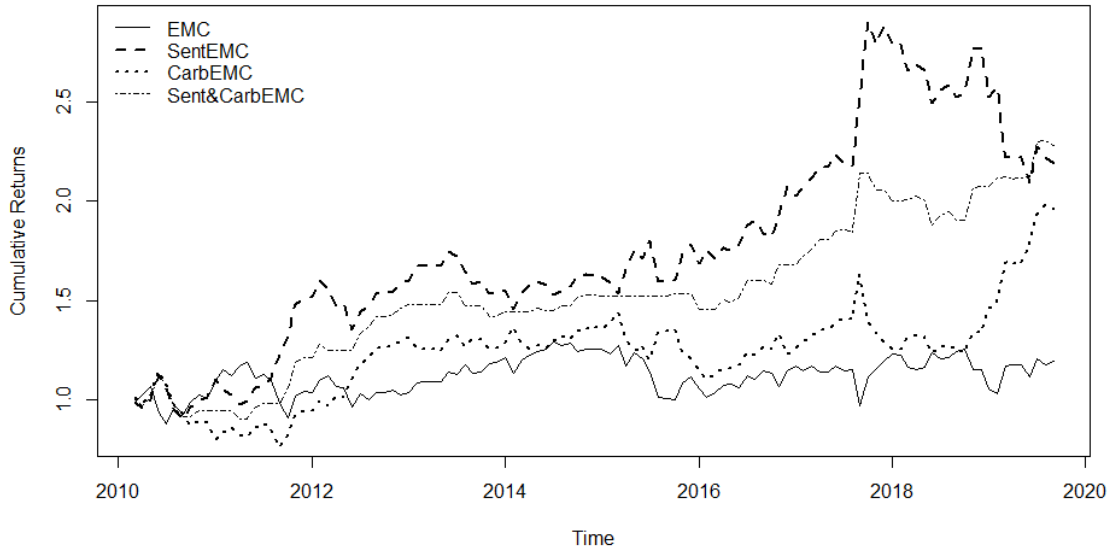
$$Ret_t^{CarbEMC} = \begin{cases} Ret_t^{EMC} & \text{if } \Delta carbon_{t-1} < 0 \\ -Ret_t^{EMC} & \text{if } \Delta carbon_{t-1} \geq 0. \end{cases} \quad (9)$$

Furthermore, we build a portfolio using the information in both investors' climate sentiment and carbon prices. Since an increase in climate sentiment and a decrease in carbon prices tend to be followed by an increase in the price of the EMC portfolio, we suggest to buy the EMC portfolio when it occurs. Differently, when we observe a decrease in investors' climate sentiment and an increase in carbon prices we suggest to sell the EMC portfolio. When changes in climate sentiment and carbon prices have the same sign, the reaction of the EMC portfolio is not clear. Hence, we suggest to invest in the risk-free security.

$$Ret_t^{Sent\&CarbEMC} = \begin{cases} Ret_t^{EMC} & \text{if } \Delta Sent_{t-1} \geq 0 \, and \, \Delta carbon_{t-1} < 0 \\ -Ret_t^{EMC} & \text{if } \Delta Sent_{t-1} < 0 \, and \, \Delta carbon_{t-1} \geq 0 \\ Ret_t^{RF} & Otherwise. \end{cases} \quad (10)$$

In Table 12, we report the average return, Sharpe ratio, and the alphas of the CAPM model, three-factors model, Carhart model, and five-factors model for the four portfolio strategies. We find that the EMC portfolio do not generate significant returns. However, when we time the investment in and out of the EMC portfolio according to information on investors' climate sentiment and carbon prices we obtain positive returns. Specifically, the Sent&CarbEMC portfolio gains 9.77% annually. Furthermore, its Sharpe ratio is more than four times larger than the Sharpe ratio of the basic EMC portfolio. These results are robust to several risk factors, indeed the portfolio produces significant alphas when we consider the CAPM model, three-factors model, Carhart model, and five-factors model.

Figure 6: Cumulative Returns Portfolio Strategies



In Figure 6, we show the cumulative returns of the four portfolio strategies. We can observe that the SentEMC and Sent&CarbEMC portfolio strategies more than double the initial investment of \$1, while the CarbEMC portfolio double it. Differently the basic EMC portfolio generates a final wealth only slightly higher than the initial investment.

Table 12: Portfolio Strategies

	EMC	SentEMC	CarbEMC	Sent&CarbEMC
Average Return	0.0028	0.0081	0.0071	0.0078^{**}
Sharpe Ratio	0.0472	0.1524	0.1328	0.2125^{**}
α_{CAPM}	0.0029	0.0085^{*}	0.0055	0.0072^{**}
α_{3F}	0.0015	0.0093^{*}	0.0070	0.0083^{**}
α_{Car}	0.0000	0.0091	0.0076^{*}	0.0085^{**}
α_{5F}	0.0020	0.0101^{**}	0.0068^{*}	0.0086^{**}

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table reports the average return, Sharpe ratio, CAPM model's alpha (α_{CAPM}), three-factors model's alpha (α_{3F}), Carhart model's alpha (α_{Car}), and five-factors model's alpha (α_{5F}) for four portfolio strategies. In the first column, we report values for the Emission-minus-Clean (EMC) portfolio which goes long on a value-weighted portfolio of emission stocks and it goes short on a value-weighted portfolio of clean stocks. In the second column, we report values for the SentEMC portfolio. This portfolio invests in the EMC portfolio if in the previous period changes in climate sentiment were positive, and it suggests to go short on the EMC portfolio otherwise. In the third column, we report values for the CarbEMC portfolio. This portfolio invests in the EMC portfolio if in the previous period changes in carbon prices were negative, and it suggests to go short on the EMC portfolio otherwise. In the fourth column, we report values for the Sent&CarbEMC portfolio. This portfolio invests in the EMC portfolio if in the previous period changes in carbon prices were negative and changes in climate sentiment were positive, and it suggests to go short on the EMC portfolio if changes in carbon prices were positive and changes in climate sentiment were negative. When changes in climate sentiment and carbon prices have the same sign, the strategy suggests to invest in the risk-free security.

5 Conclusions

Despite broad consensus in the scientific community on the occurrence of climate change, there is still substantial disagreement in the general public. The Yale Climate Opinion Maps 2018 (Howe et al., 2015) report that 70% of the Americans believe that global warming is happening and that it will harm future generations. However, this percentage drop to 41% among Conservative Republican. Moreover, only 41% of the Americans think that global warming will harm them personally, while 48% disagree.

Climate change is the biggest challenge of our times, and it requires a change in attitudes and behaviour of everyone. This paper wants to explore how financial markets can help in achieving the global climate targets. Since investors have limited attention and climate risk is difficult to assess, it is crucial understanding investors' reactions to events and how these reactions are translated into trading activities.

We measure investors' climate sentiment through sentiment analysis on StockTwits posts on climate change and global warming. We find that investors' climate sentiment is higher either when an international environmental disasters occurs or there is an international event related to climate change. These findings suggest that natural disasters as well as international events such as the global climate strikes may reduce skepticism on the matter and increase awareness. Moreover, we observe that an increase in climate sentiment causes a short term undervaluation of emission stocks and overvaluation of clean stocks. When investors have a higher awareness and a more positive attitude towards climate change and global warming they may allocate their resources in favour of clean stocks rather than emission stocks. This is similar to what the literature has documented for sin stocks (companies involved in producing alcohol, tobacco, and gaming). Indeed, ethical investors tend to exclude sin stocks, as the companies involved are thought to be making money from exploiting human weaknesses and vices (Fabozzi et al., 2008; Hong and Kacperczyk, 2009; Statman and Glushkov, 2009). Furthermore, investors may expect that emission stocks will have lower cashflows in the future because of the losses generated by climate change, higher costs of future emissions and tighter environmental regulations.

Additionally, the results show that emission stocks are sensitive to variation in carbon prices because of their high carbon risk. We also observe that investors' climate sentiment causes an increase in carbon prices. The more the investors are aware of the challenges presented by climate change and global warming the more the carbon price increases which should deter firms from rising CO_2 emissions.

Finally, we find that timing the investment in and out of the EMC portfolio according to information on investors' climate sentiment and carbon prices produces significantly positive returns. Specifically, the portfolio strategy gains 9.77% annually.

In summary, this paper shows the importance of investors' climate sentiment and its effects on financial markets. Policy-makers should promote initiatives aiming at increasing public awareness on climate change. On the other hand, they should raise the price of CO_2 and other greenhouse-gas emissions. Furthermore, firms should disclose information on their climate risk and level of carbon emissions to reduce information asymmetry and improve efficiency.

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A Industry classification

Table 13: Summary of Industry Information

ICB Code	Industry Name	IPCC Category 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
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)

Notes: The table presents a list of Industry Classification Benchmark (ICB) codes available from Thomson Reuters Datastream and the matching IPCC category codes which are classified as carbon intensive.

B Environmental Disasters, International Events and US Environmental Policies

Table 14: Events

Date	Event	Disasters	Intern.	Policies
01/01/2010	Stronger smog standard	0	0	1
01/04/2010	BP oil spill	1	0	0
01/10/2010	Nation's First Greenhouse Gas Fuel Efficiency Standards for Trucks and Buses	0	0	1
01/11/2010	Greenhouse gas reporting	0	0	1
01/12/2010	UN Climate Change Conference	0	1	0
01/03/2011	Japanese Earthquake, Tsunami Damage Nuclear Reactor	1	0	0
01/05/2011	Next Generation of Fuel Economy Labels Unveiled	0	0	1
01/07/2011	Smokestack Pollution Reduced,Protecting Americans' Health from Soot and Smog	0	0	1
01/08/2011	Fuel Efficiency and Greenhouse Gas Pollution Standards for Heavy-Duty Vehicles	0	0	1
01/12/2011	UN Climate Change Conference	0	1	0
01/03/2012	EPA Proposes First Carbon Pollution Standard for New Power Plants	0	0	1
01/04/2012	EPA Updates Air Pollution Standards for Oil and Natural Gas	0	0	1
01/08/2012	Obama Administration Finalizes Historic 54.5 mpg Fuel Efficiency Standards	0	0	1
01/09/2012	Arctic Sea ice shrinks to a record minimum	1	0	0
01/11/2012	UN Climate Change Conference	0	1	0
01/12/2012	EPA Strengthens Air Standards for Fine Particles, Reducing Harmful Soot Pollution	0	0	1
01/06/2013	Comprehensive Plan for Climate Change	0	0	1
01/09/2013	IPCC fifth assessment	0	1	0
01/11/2013	UN Climate Change Conference	0	1	0
01/01/2014	Spill of methyl cyclohexane in Charleston	1	0	0
01/04/2014	New Rules for Cleaner Fuels and Cars	0	0	1
01/06/2014	First Guidelines Proposed to Cut Carbon Pollution from Existing Power Plants	0	0	1
01/09/2014	UN Climate Summit and People's Climate March	0	1	0
01/11/2014	US-China Agreement on Climate Change	0	0	1
01/12/2014	UN Climate Change Conference	0	1	0
01/02/2015	Keystone XL veto	0	0	1
01/05/2015	Pope Francis issues *Laudito Si* environmental encyclical	0	1	0
01/09/2015	EPA issues notice of violation to Volkswagen	0	0	1
01/11/2015	President Obama rejected TransCanada's Keystone XL Pipeline Proposal	0	0	1
01/11/2015	Global Climate Strike	0	1	0
01/12/2015	UN Climate Change Conference and Paris Agreement	0	1	0
01/04/2016	Paris Climate Accord	0	1	0
01/06/2016	President Obama Signs Lautenberg Chemical Safety for the 21st Century Act	0	0	1
01/11/2016	UN Climate Change Conference	0	1	0
01/03/2017	Trump signed a presidential permit to allow TransCanada to build the Keystone XL pipeline	0	0	-1
01/05/2017	14 states signed a petition urging the President Trump to stay in the Paris Agreement	0	0	1
01/06/2017	US Withdraws from the Paris Climate Accord	0	0	-1
01/10/2017	EPA Proposes Repeal of the Clean Power Plan	0	0	-1
01/11/2017	UN Climate Change Conference	0	1	0
01/01/2018	EPA loosens regulations on toxic air pollution	0	0	-1
01/04/2018	EPA starts rollback of car emissions standard	0	0	-1
01/07/2018	Trump officials propose rollbacks of endangered species act rules	0	0	-1
01/08/2018	Trump announces plan to weaken Obama-era fuel economy rules	0	0	-1
01/09/2018	EPA repeals Obama-era methane rules	0	0	-1
01/10/2018	President Trump signs bill to clean up ocean plastics	0	0	1
01/12/2018	Trump administration rolls back Obama-era coal rules	0	0	-1
01/12/2018	UN Climate Change Conference	0	1	0
01/03/2019	Global Climate Strike	0	1	0
01/04/2019	Trump signs pipeline orders	0	0	-1
01/04/2019	Earth Day partnered with National CleanUp Day and Keep America Beautiful	0	1	0
01/05/2019	Offshore drilling safety rules rolled back	0	0	-1
01/05/2019	Global Climate Strike	0	1	0
01/08/2019	Amazon rain forest wildfires	1	0	0
01/09/2019	Global Climate Strike	0	1	0

Notes: The table reports a list of the environmental disasters, international events on climate change, and US environmental policies.

C Sentiment Analysis

In this paper, we use the R package sentimentr (Rinker, 2019). 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. 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 (-), demand (-), demanded (-), demands (-), director (+), economic (-), fight (-), fighting (-), fuels (+), global (+), gore (-), government (-), information (+), intended (-), legal (+), like (+), management (+), partner (+), pollution (+), pretty (+), share (+), shares (+), state of the art (+), 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): antisemitic (-), arse (-), avoiding (-), beat (+), boom (+), booming (+), bull shit (-), bullish (+), bullsht (-), bullsh (-), conscious (+), cost (-), earning (+), earnings (+), eco-friendly (+), feel like (neutral), fight (+), fighting (+), grew (+), grown (+), healthier (+), hurdle (-), i like (+), lol (+), negatively (-), profit (+), profits (+), rig (-), rigged (-), rises (+), rose (+), risen (+), sceptic (-), scepticism (-), smiley (+), snow job (-), supreme court (neutral), tech (+), technologies (+), they like (+), vice president (neutral), weapon (-), weaponize (-), weaponized (-), we like (+), wink (+), you like (+).

In addition to this, we replace emoticons with their word equivalent through the replace_emoticon() command, so as to be included in the score computation.

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).