Attention to Global Warming*

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Abstract

We propose that people update their beliefs about climate change when there are attention-grabbing weather events in their area. The effects of long-term global warming may be overlooked in normal times, but people revise their beliefs upwards when experiencing warmer than usual temperatures. Using international data, we show that attention to climate change, proxied by Google and Bloomberg search volume, goes up when the local temperature is abnormally high. In financial markets, stocks of carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather. Our study can shed light on understanding collective beliefs and actions in response to global warming.

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1 Introduction

On December 28, 2017, U.S. President Donald Trump, who has called global warming a "hoax" on multiple occasions, wrote the following message on Twitter when unusually cold temperatures were expected to hit the Eastern U.S.:

> In the East, it could be the COLDEST New Year's Eve on record. Perhaps we could use a little bit of that good old Global Warming that our Country, but not other countries, was going to pay TRILLIONS OF DOLLARS to protect against. Bundle up!

"But Mr. Trump's tweet made the common mistake of looking at local weather and making broader assumptions about the climate at large," writes *The New York Times*.[1] President Trump is not the only one making this mistake. Global warming is a long-term trend that is usually not visible on a personal level. In contrast, local temperature of a given month or year is more noticeable, although it is less relevant for the trend and can be caused by reasons unrelated to global warming, e.g., ocean oscillations such as the El Niño Southern Oscillation, ENSO (IPCC, 2014; Schmidt, Shindell, and Tsigaridis, 2014). For example, a record-breaking warm month of July in New York City is unlikely to have much information about the increase in average global temperature in the next decade. The local temperature in July is, however, more visible than the 10-year global trend to New Yorkers.

In this paper, we measure people's reaction to abnormally high local temperatures by examining attention to climate change and stock prices. Our data cover 75 cities in the world with major stock exchanges. The advantage of using attention and financial data is that we can estimate people's opinions at a high frequency (unlike surveys) and study their follow-up actions, as investors trade on their beliefs and move stock prices. Human's collective belief and effort are important determinants of how successful climate policies and campaigns can be. Our study aims to empirically identify how the general public realizes and responds to

[1] "It's Cold Outside. Cue the Trump Global Warming Tweet." *The New York Times*, December 28, 2017.

the impacts of global warming.

Since attention is limited, people are likely to focus more on attention-grabbing weather events and personal experiences when revising their beliefs towards global warming. These situations are people's first-hand personal experiences of weather, and the impact can be amplified through communication channels and the media.[2] Extreme local weather events therefore serve as "wake-up calls" that alert investors to climate change. Our paper tests this idea in two steps: first, we test whether people pay more attention to climate change when experiencing warm weather. The second set of analyses examines if this extra attention translates into impact on financial markets; because of the home bias (see, e.g., the review by Karolyi and Stulz, 2003), prices of local stocks are affected by local investors.

Our results show that, during abnormally warm months in their area, people search and read more information related to global warming.[3] This applies to both retail and institutional investors. Google search volume, which comes mostly from households, of the topic "Global Warming" goes up when the local weather is unusually warm. Institutional investors also pay more attention to carbon-intensive firms, as reflected by Bloomberg activity on these stock tickers, when the exchange city experiences abnormally warm temperatures. Both of these effects are more prominent when the local abnormal temperature is in the top quintile.

When investors revise their beliefs about global warming, they may buy firms with lower climate sensitivities and sell firms with higher climate sensitivities, such that the former outperforms the latter. We sort stocks into high- and low-climate sensitivities according to their MSCI Carbon Emission Score, which captures companies' green house gas emissions and is adjusted by industry. Both our stock-level and portfolio-level tests show that stock prices of carbon-intensive firms (whose emissions are in the top tercile in the exchange city) decrease relative to the benchmark in abnormally warm months at the local exchange. The

[2]Media attention to climate change appears to be higher in record-breaking warmest years than in non-record years (Schmidt, 2015).

[3]In this paper, we refer the term "abnormally warm" to cases in which a region's temperature is significantly higher than the historical average temperature at the same point of the year.

effect is again more prominent when the local abnormal temperature is in the top quintile: comparing to months in the lowest (i.e., coolest) temperature quintile, carbon-intensive firms underperform by 0.85%–1.81% in size-adjusted returns in these months. This price pattern does not seem to reverse in the longer term.

The idea that investors pay more attention to local weather events is consistent with experiential learning, which is supported by recent literature on climate change. Zaval, Keenan, Johnson, and Weber (2014), Akerlof et al. (2013), and Myers et al. (2012) show that personal experience of global warming reported in surveys leads to increased perception of climate risk in the U.S., which is confirmed by Broomell, Budescu, and Por (2015) and Howe et al. (2013) using international surveys that cover 24 countries and 89 countries, respectively. Konisky, Hughes, and Kaylor (2016), Borick and Rabe (2014), and Joireman, Truelove, and Duell (2010) find a similar relationship using objective measures of personal weather experience such as outdoor temperature, snowfall, and occurrences of floods and hurricanes. Li, Johnson, and Zaval (2011) further show that perceived deviations from normal temperature not only alter beliefs but are also followed by actions: participants are more likely to donate their earnings to a global-warming charity. Beliefs about global warming in all these studies are measured by surveys. In contrast, our paper uses objective proxies for attention to capture the learning process, and we can examine how updated aggregate beliefs are reflected in prices. Under experiential learning, people start the learning process based on concrete experience, and form abstract concepts through observing and analyzing information before taking action (Boud, Keogh, and Walker, 1985; Kolb, 1984). In our context, we are able to see if people read more about global warming (from the Internet) after their experiences of weather.

This paper complements previous empirical findings on reactions to climate and other external conditions. Chang, Huang, Wang (2017) find that more health insurance contracts are sold when air pollution is high but they are more likely to be canceled if air quality improves shortly afterwards. Busse, Pope, Pope, and Silva-Risso (2015) and Conlin, O'Donoghue, Vogelsang (2007) show that the choice to purchase warm- or cold-weather vehicle types and cold-weather clothing, respectively, depends on the weather at the time of purchase. Hong, Li, and Xu (2017a, b) document underreaction of food companies' stock prices and sales forecasts to trends in droughts exacerbated by global warming. Our preliminary results are also in line with general underreaction to global warming. Finally, the finding that people pay more attention and the differential impacts on the cross-section of stocks distinguish our work from the literature that links weather-induced investor mood and the stock market (Kamstra, Kramer, and Levi, 2003; Goetzmann, Kim, Kumar, and Wang, 2015, etc.).

The rest of the paper is structured as follows. Section 2 discusses our research design. International temperature, attention, and financial data are described in Section 3. Section 4 presents the results. Section 5 concludes.

2 Methodologies and research design

We would like to identify investor reaction to global warming in warm local weather. The reaction is first measured by monthly Google Search Volume Index (SVI) of the topic "Global Warming" in a city, which proxies for people's attention. This idea follows Da, Engelberg, and Gao (2011), who use SVI of tickers to study investor attention.[4] We also capture institutional attention to specific stocks by their Bloomberg news searching and reading activity (following Ben-Rephael, Da, and Israelsen, 2017). Weather conditions are measured by average daily temperature in each city in each month. To better understand the learning process, we decompose local monthly temperature into 3 components, which account for predictable and seasonal patterns. For example, for temperature in city i in

[4]Several other papers also look at Google search volume of global warming and climate change and relate it to local weather conditions: e.g., Lineman, Do, Kim, and Joo (2015), Cavanagh et al. (2014), Herrnstadt and Muehlegger (2014), Lang (2014), and Kahn and Kotchen (2011). These studies focus on U.S. data while our paper covers 75 cities worldwide.

month t, we define:

$$Temperature_{it} = Average\_Temp_{it} + Monthly\_Temp_{it} + Abnormal\_Temp_{it}, \quad (1)$$

where $Average\_Temp_{it}$ is the average monthly local temperature in city i over the 120 months prior to t; $Monthly\_Temp$ is the average temperature deviation of this month from the average, i.e., the average temperature in city i in the same calendar month over the last 10 years minus $Average\_Temp_{it}$; and $Abnormal\_Temp_{it}$ is the remainder.[5] Our focus is how local abnormal temperature, which captures people's new experience, affects attention (as proxied by the change in SVI and variables constructed from Bloomberg), while controlling for $Average\_Temp_{it}$ and $Monthly\_Temp_{it}$.

Then we turn to investor reaction in the stock market. Specifically, we look at the cross-section of firms with different sensitivities to climate change. The effect of climate on stock prices can happen through multiple channels that are not mutually exclusive. First, if a persistent increase in temperature represents systematic risk, then high-climate-beta stocks should earn a higher risk premium than low-climate-beta stocks, as shown by Bansal, Kiku, and Ochoa (2016) and Bansal, Ochoa, and Kiku (2016). Second, regulations on emissions can be tightened when the threat of global warming is more serious, e.g., the Paris Agreement would make the production cost of carbon-intensive firms higher and their future cashflows lower. Finally, socially responsible investors may stay away from firms that are climate friendly, in a way similar to "sin" stocks (those involved in producing alcohol, tobacco, and gaming) being shunned by some institutions (Hong and Kacperczyk, 2009). In this paper we report results based on the assumption that firms with high (low) carbon emissions are more (less) prone to climate change.

We examine monthly size-adjusted stock returns under warm weather. If investors start recognizing the effect of climate on financial markets and buy low-climate-sensitivity and sell high-climate-sensitivity firms, the former will earn higher returns than the latter. We study

[5] All of our results hold if we use all temperature observations instead of a rolling 10-year window.

the short-term as well as the long-term pattern to see if there is any reversal. A reversal may indicate that the short-term price changes overshoot, which implies temporary inefficient allocation of resources in response to global warming.

3 Data

Our data come from various sources. In the following, we introduce the databases we use, as well as the variables we obtain and examine in our analyses.

Weather

We obtain daily weather data from the Global Surface Summary of Day Data, produced by the National Climatic Data Center (NCDC). The input data used in building these daily observations are the Integrated Surface Data (ISD), which contain weather records from over 9,000 stations globally. The weather conditions include temperature, wind, cloudiness, precipitation, snow depth, and others. The data is available since 1929. For our analysis, we collect the daily temperature data for 75 cities with major stock exchanges. By identifying the location coordinates, we select the closest weather station to the address of the exchange.

Carbon emission

We get firms' carbon emission estimates from MSCI ESG Ratings, which analyze companies' environmental, social, and governance issues. Specifically, MSCI ESG studies greenhouse gas (GHG) emissions of more than 8,600 companies worldwide. They collect data once a year from most recent corporate resources such as annual reports and corporate social responsibility reports. When direct disclosure is not available, they use GHG data reported by the Carbon Disclosure Project or government databases. The Carbon Emission Score on a scale of 0–10 is given to each firm in each year.[6] Companies with better performance on

[6]Note that MSCI does not assign a score to every public firm: for example, the coverage in the U.S. increases from 461 in 2007 to 840 in 2015. While MSCI also issues other climate-change related scores to companies, such as Climate Change Theme Score, the Carbon Emission Score is the one which is available for the longest period.

this issue score higher. The score is adjusted by industry, and thus is comparable for two firms from different industries. The data is available since 2007.

Google search volume index

To capture households' attention to climate change, we track their related search activity on Google. The data source is Google Trend, which provides a Search Volume Index (SVI) of the search topic of "Global Warming" since 2004. We download the monthly SVI in each of the 75 locations from 2004 to 2016.[7]

Bloomberg activity

We follow Ben-Rephael, Da, and Israelsen (2017) to measure abnormal institutional investor attention (AIA). Bloomberg provides information on the news searching and reading activities of their users for specific (U.S. and international) stocks since February 17, 2010. Bloomberg uses hourly counts of news articles read and searched for each stock and assigns a Daily Max Readership (DMR) score of 0, 1, 2, 3, and 4 to track the intensity of abnormal attention. As defined by Ben-Rephael, Da, and Israelsen (2017), AIA is a dummy variable at daily frequency with the value of one if Bloomberg's DMR score is 3 or 4, and zero otherwise. In addition, we use the continuous variable version of AIA—$AIAC$, which is transformed from Bloomberg's 0 to 4 scores under the normal distributional assumption. The raw DMR scores provided by Bloomberg are also used in our tests as an alternative institutional attention measure. All three measures, AIA, DMR and $AIAC$, are on a daily basis, and we take an average of each company in each month.

Stock and company information

Monthly stock returns, market capitalization, and industry information are available from Thomson Reuters DataStream. DataStream covers more than 100,000 equities in nearly 200 countries from 1980 onwards. The literature points out that DataStream may suffer from

[7] All searches are at the city level, except for some small countries where the search volume data are only available at the country level.

data errors. We winsorize raw returns at the top and bottom 2.5% in each exchange in each month.

4 Empirical Results

Our tests aim to investigate two questions: (1) whether people's attention varies with local temperatures, and (2) if any, how the temperature-induced attention affects the stock price of firms in the same city. Given that climate change is a global phenomenon, it is critical to conduct our study in an international setting, in order to understand people's collective beliefs and reactions to the issue. The international setting also gives us an additional identification advantage: climate science research shows that extreme temperatures rarely occur simultaneously in both Northern and Southern Hemispheres (see, e.g., Neukom et al., 2014). Table I shows the list of 75 cities in our sample. In all regressions below, all standard errors are clustered by exchange city and year-month.

4.1 Attention and local temperatures

We first test whether local temperatures influence people's attention to the issue of global warming and climate change. We use two measures of attention. The first two are Google Search Volume Index (SVI) of the topic of "global warming" and the Abnormal Institutional Attention (AIA) from Bloomberg. AIA measures how frequently Bloomberg users, who are likely financial institutions, search and read information about a certain firm.

First, we run the following regression based on Google data:

$$DSVI_{it} = \alpha + \beta_1 Average\_Temp_{it} + \beta_2 Monthly\_Temp_{it} + \beta_3 Abnormal\_Temp_{it} + \epsilon_{it}, \quad (2)$$

where $DSVI_{i,t}$ is the log change of SVI in city i in month t, adjusted for seasonality;[8]

[8] $DSVI$ is defined as the residuals from the regression of log change of monthly SVI on month-of-the-year dummies. The residuals are then winsorized at the top and bottom 2.5% tails. Two cities, Shenzhen and

$Average\_Temp_{it}$, $Monthly\_Temp_{it}$, and $Abnormal\_Temp_{it}$ are the decomposition of temperature in city i in month t according to Eq.(1). Our coefficient of interest is β_3. Regression results are reported in Table II. In Column (1) of Panel B, the coefficient estimate of $Abnormal\_Temp$ is significantly positive (t-stat = 2.3). The result suggests that people or retail investors pay more attention to global warming when they are experiencing abnormally high temperature. The result is robust if we include year fixed-effects in Column (2) and year-month fixed effects in Column (3), which focus more on the geographic variation. As a side note, neither $Average\_Temp$ nor $Monthly\_Temp$, the predictable parts of temperature based on past data, is statistically significant.

In Column (4), we rank all months into quintiles based on $Abnormal\_Temp$ in the city and include quintile dummies in the regression. The coefficients of quintile dummies indicate that the temperature effect is non-linear: the coefficients of quintiles 2 and 3 are not significantly different from zero, while the coefficient of quintile 4 is 2.67 (t-stat = 1.4). The coefficient of the highest temperature quintile dummy equals 3.27 (t-stat = 1.8). Thus, our results suggest that Google search volume increases with the highest abnormal local temperatures, which are the most salient. This idea is similar in spirit to the "frog in the pan" hypothesis proposed by Da, Gurun, and Warachka (2014), who show that investors pay more attention to infrequent dramatic changes than to frequent gradual changes.

It is worth noting the economic magnitude: based on the estimation in Column (4), compared to the 20% abnormally coolest months, in the 20% abnormally warmest months people search more about global warming by 3.3%, or about 4.7% of its standard deviation (which is 69.5%, shown in Panel A).

We next examine how institutional attention reacts to local abnormal temperatures. Finance professionals may also have limited attention: for example, Hong, Li, and Xu (2017b) show that analysts and managers underreact to drought trends when making sales forecasts. Although Bloomberg does not provide the location of searching and reading activity, many

Shanghai, are dropped from the analysis because there are no valid local Google search data.

of the institutional investors should be located near the local exchange and affected by its weather conditions. We conduct the test using the contemporaneous local abnormal temperature:

$$AIA_{jt} = \alpha + \beta_1 Average\_Temp_{jt} + \beta_2 Monthly\_Temp_{jt} + \beta_3 Abnormal\_Temp_{jt} + \beta_4 AIA_{j,t-1} + \epsilon_{jt}, \tag{3}$$

where $Average\_Temp_{jt}$, $Monthly\_Temp_{jt}$, and $Abnormal\_Temp_{jt}$ are the decomposition of temperature in the city where stock j is traded in month t. We run separate regressions with high- and low- carbon emission firms, which are defined as firms whose MSCI carbon emission scores at the previous year-end are in the lowest tercile and in the highest tercile, respectively. Year-month fixed effects are included.

We use three versions of institutional attention: Daily Max Readership (DMR), Abnormal Institutional Attention (AIA), and the continuous variable version of AIA ($AIAC$). Table III reports the results for high emission firms (Panel B) and low emission firms (Panel C). In Column (1) of Panel B, the coefficient of $Abnormal\_Temp$ is significantly positive (t-stat = 3.1). The results using alternative measures, i.e., AIA and $AIAC$, are similar and significant; see Columns (2) and (3). In Columns (4)–(6), $Abnormal\_Temp$ are replaced by quintile dummies, as in Table II. Again the coefficients of the highest temperature quintile are the strongest. In terms of economic magnitude, from Column (4), a change from the lowest to the highest quintile of abnormal temperature is associated with a 0.0272 increase in DMR, or approximately 3.7% of its standard deviation (which is 0.73, shown in Panel A). In Panel C, the coefficients of $Abnormal\_Temp$ are insignificant in regressions with low emission firms (although Quintile 2 is significant in some regressions, there is no systematic pattern). Taken together, we find that abnormally warm weather leads to more institutional attention on high emission firms but not on low emission firms, which is in line with our return results in Section 4.2 and consistent with updated beliefs about climate change.

4.2 Pricing effect of temperature-induced attention

We next examine whether extra attention affects stock prices, focusing on the differential reactions in carbon-intensive firms and low emission firms. As discussed in Section 2, we expect that updated beliefs about global warming will make stocks of high emission firms underperform stocks of low emission firms. High- (low-) carbon emission firms are defined as firms whose MSCI carbon emission scores at the previous year-end are in the lowest (highest) tercile, as in Section 4.1. The sample period is January 2008–June 2016. Again we capture investors' experience by using the local temperature in the city where the exchange is located, similar in spirit to Hirshleifer and Shumway (2003) and Saunders (1993).

We first run regressions at the stock level:

$$Adjusted\_Ret_{jt} = \alpha + \beta_1 Average\_Temp_{jt} + \beta_2 Monthly\_Temp_{jt} + \beta_3 Abnormal\_Temp_{jt} + \epsilon_{jt}, \tag{4}$$

where $Adjusted\_Ret_{jt}$ is the size-adjusted return of stock j in month t;[9] $Average\_Temp_{jt}$, $Monthly\_Temp_{jt}$, and $Abnormal\_Temp_{jt}$ are the decomposition of temperature in the city where stock j is traded in month t. Year-month fixed effects are included. The results are in Table IV. Columns (1) and (2) of Panel B show that higher abnormal local temperature is associated with lower size-adjusted returns in high emission firms and the effect is the strongest in the highest temperature quintile. There is a sizable economic impact, with a change from temperature quintile 1 (coolest) to quintile 5 (warmest) corresponding to a drop of 85bps in size-adjusted return. In Columns (3) and (4), the effect of $Abnormal\_Temp$ is generally insignificant for low emission firms. The return patterns in month t are consistent with the reactions in attention measures documented in Section 4.1: extra attention paid to carbon-intensive firms when the local temperature is abnormally high, particularly in the

[9] In this paper we use size-adjusted returns, defined as the stock's return in month t minus the average return of stocks in the same size quintile in the exchange. Market cap data are obtained from DataStream and have better coverage than other financial data. In the future, we may use other models to calculate adjusted returns (e.g., a factor model that is based on momentum and cashflow-to-price, Hou, Karolyi, and Kho, 2011). One disadvantage is that the sample size would be greatly reduced when requiring other company information (on top of the MSCI scores we use).

warmest months, is associated with lower contemporaneous returns in these firms.

We further confirm these findings by forming portfolios that are long in high emission stocks and short in low emission stocks (the portfolios are called EMC, EMISSION Minus CLEAN). Then we run the following regression:

$$EMC_{it} = \alpha + \beta_1 Average\_Temp_{it} + \beta_2 Monthly\_Temp_{it} + \beta_3 Abnormal\_Temp_{it} + \epsilon_{it}, \quad (5)$$

where EMC_{it} refers to the equal- or value-weighted portfolio (size-adjusted) return in city i in month t. The temperature variables are calculated from contemporaneous temperature in city i in month t. Year-month dummies are included. Panel A of Table V reports the summary statistics.[10] One can notice that during the sample period, carbon-intensive firms underperform low emission firms; Mean EMC equals -43bps per month for equal-weighted portfolios and -31bps for value-weighted. Also, the underperformance is mainly driven by low returns of high emission firms, not by high returns of low emission firms. This pattern is consistent with the evident global warming trend in the recent decade and reflects increasingly higher costs of carbon emissions.

Panel B presents the result of Eq.(5). Both equal- and value-weighted portfolios show negative returns during an abnormally warm month, with the most prominent effect in the highest quitile. The coefficients in Columns (2) and (4) suggest that high-emission firms relatively underperform by 1.81% (equal-weighted) and 1.46% (value-weighted) in the top 20% abnormally warmest months, more than four times the average EMC returns in Panel A.

One concern is that the result can be driven by two trends: EMC is more negative in recent years as price of carbon has gone up and abnormal temperature also occurs more frequently later in the sample. Note that our test already includes year-month fixed effects.

[10] The drop in the sample size is due to missing return and size data from DataStream. In Table IV, high (low) emission firms come from 62 (55) unique exchanges. In Table V, we require an exchange to have more than 5 stocks in each of the EMISSION and CLEAN portfolios, valid market cap data, and returns data for six continuous months. These criteria leave us with 19 unique exchanges.

Our future tests will directly control for the price of carbon, which can be measured by carbon futures price of contracts traded on Intercontinental Exchange (ICE) Futures Europe. In Panel C emission and clean portfolio returns are presented separately. We find that the result is mostly driven by lower returns of high emission firms, rather than better performance of low emission firms.

Finally, we examine the long-term performance subsequent to an abnormally warm month, both at the stock level (for each high emission stock j) and the portfolio level (for equal-weighted EMC in each city i):

$$Adjusted\_Ret_{j,t+1,t+n} = \alpha + \beta_1 Average\_Temp_{jt} + \beta_2 Monthly\_Temp_{jt} + \beta_3 Abnormal\_Temp_{jt} + \epsilon_{jt}, \tag{6}$$

$$EMC_{i,t+1,t+n} = \alpha + \beta_1 Average\_Temp_{it} + \beta_2 Monthly\_Temp_{it} + \beta_3 Abnormal\_Temp_{it} + \epsilon_{it}, \tag{7}$$

where $n = \{3, 6\}$. If β_3 is negative or zero, it is more consistent with the belief updating story: investors with limited attention generally overlooks climate risk, but recognizes it when reacting to attention-grabbing weather events. Otherwise if β_3 appears to be positive, it is more consistent with the overreaction story as the previous price pattern at t has reversed. Table VI presents the result.

As shown in Panels A and B, the coefficients of $Abnormal\_Temp$ or the qunitile dummies are always statistically insignificant, indicating that there is no strong reversal in the three to six months after month t. However, some coefficients are positive, with a magnitude that is comparable and sometimes slightly larger than that in month t (for example, compare the coefficient of $Abnormal\_Temp$ in Column (2) of Panel A with that in Column (1) in Table IV, Panel B). It may indicate that some overreaction is not detected in the return data, and it calls for an analysis using investors' trading behavior. In future tests, we will study trading activity of high-emission firms using U.S. mutual fund and other institutional investors' holdings (available from Thomson Reuters Mutual Fund Holdings (S12) and Thomson Reuters

Institutional Holdings (13F)) and international institutional investors' holdings (available from Factset).

5 Conclusion

Global warming is an important long-term issue that requires collective action to address. Scientists show that human influence is the dominant cause of global warming (Intergovernmental Panel on Climate Change, IPCC, 2014; Cook et al., 2013; Oreskes, 2004), and this is evident from the emission of greenhouse gases such as CO_2 from human activities. Despite all the scientific facts and evidence, it is not clear whether people treat climate risk seriously and react to it—a U.S. survey (Yale Program on Climate Change Communication, 2016) estimates that only 70% of adults believe that global warming is happening, and 40% think it will harm them personally. Our paper aims to understand how people update their beliefs about climate change.

We show that people revise their beliefs upwards when the local temperature is unusually warm. There is higher Google search activity on the topic "Global Warming," as well as higher Bloomberg news searching and reading activity on stock tickers of firms that have high carbon emission. In financial markets, carbon-intensive firms underperform in the month when the exchange city is abnormally warm. These findings are consistent with limited attention, under which people focus on attention-grabbing weather events and personal experiences. While climate change is a long-term trend, local weather is more visible even though it may not be relevant for the global trend.

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Table I. List of exchange cities

This table lists the exchange cities that we use in analyses.

Exchange City	*Country/Region*	*Continent*
Amman	Jordan	Asia
Amsterdam	Netherlands	Europe
Athens	Greece	Europe
Bangkok	Thailand	Asia
Belgrade	Serbia	Europe
Berlin	Germany	Europe
Bern	Switzerland	Europe
Bogota	Columbia	South America
Bratislava	Slovakia	Europe
Brussels	Belgium	Europe
Bucharest	Romania	Europe
Budapest	Hungary	Europe
Buenos Aires	Argentina	South America
Bulgarian	Bulgaria	Europe
Busan	Korea	Asia
Cairo	Egypt	Africa
Colombo	Sri Lanka	Asia
Copenhagen	Denmark	Europe
Cyprus	Cyprus	Europe
Dhaka	Bangladesh	Asia
Dublin	Ireland	Europe
Dusseldorf	Germany	Europe
Frankfurt	Germany	Europe
Hamburg	Germany	Europe
Hanoi	Vietnam	Asia
Helsinki	Finland	Europe
Ho Chi Minh	Vietnam	Asia
Hong Kong	Hong Kong	Asia
Istanbul	Turkey	Europe
Jakarta	Indonesia	Asia
Johannesburg	South Africa	Africa
Karachi	Pakistan	Asia
Kiev	Ukraine	Europe
Kuala Lumpur	Malaysia	Asia
Kuwait	Kuwait	Asia
Lagos	Nigeria	Africa
Lima	Peru	South America
Lisbon	Portugal	Europe
Lithuania	Lithuania	Europe

Ljubljana	Slovenia	Europe
London	U.K.	Europe
Luxembourg	Luxembourg	Europe
Madrid	Spain	Europe
Manila	Philippines	Asia
Mexico City	Mexico	North America
Milan	Italy	Europe
Moscow	Russia	Europe
Mumbai	India	Asia
Munich	Germany	Europe
Muscat	Oman	Asia
Nagoya	Japan	Asia
New York	U.S.	North America
Osaka	Japan	Asia
Oslo	Norway	Europe
Paris	France	Europe
Prague	Czechia	Europe
Riyadh	Saudi Arabia	Asia
Santiago	Chile	South America
Sao Paulo	Brazil	South America
Shanghai	China	Asia
Shenzhen	China	Asia
Singapore	Singapore	Asia
Skopje	Macedonia	Europe
Stockholm	Sweden	Europe
Stuttgart	Germany	Europe
Sydney	Australia	Oceania
Taipei	Taiwan	Asia
Tel Aviv	Israel	Asia
Tokyo	Japan	Asia
Toronto	Canada	North America
Vienna	Austria	Europe
Warsaw	Poland	Europe
Wellington	New Zealand	Oceania
Zagreb	Croatia	Europe
Zurich	Switzerland	Europe

Table II. Google search volume of "global warming" and abnormal temperature

This table reports the result of analyses on the effect of abnormal temperature on Google search volume of "global warming". Panel A presents summary statistics of variables. $DSVI$ is monthly log change of Google's search volume index (SVI) of the topic "global warming" and adjusted for seasonality. *Average_ Temp* is the average monthly temperature (in Fahrenheit degrees) of the exchange's city over the past 120 months. *Monthly_ Temp* is the city's average temperature in the same month of the year over the past 10 years minus *Average_ Temp*. *Abnormal_ Temp* is the city's temperature in this month minus *Average_ Temp* and *Monthly_ Temp*. Panel B represents the result of regressing $DSVI$ on temperature measures. For each exchange city, months are sorted into quintiles based on *Abnormal_ Temp*, and *Abnormal_ Temp Quintile 2-5* are quintile dummies which equal one if the month belongs to quintile 2-5, respectively. The sample is from 2004 to 2016. Standard errors are clustered by exchange city and by year–month, and the corresponding t-statistics are reported in parentheses.

Panel A: Summary statistics

	Mean	S.D.	P10	P25	P50	P75	P90	N
DSVI (%)	-0.042	69.539	-52.739	-23.916	-0.635	22.894	53.511	11315
Average_ Temp	61.3	12.7	47.2	50.8	57.7	72.9	81.6	11315
Monthly_ Temp	0.069	10.944	-15.317	-8.459	0.193	8.358	15.583	11315
Abnormal_ Temp	0.292	2.747	-2.836	-1.225	0.244	1.735	3.562	11315
# of unique exchanges	73							

Panel B: Regression of $DSVI$ on abnormal temperature

Dep. Var.: DSVI (%)	(1)	(2)	(3)	(4)
Average_ Temp	0.00725	0.00801	0.00751	-0.000617
	(0.87)	(0.96)	(0.66)	(-0.05)
Monthly_ Temp	0.00633	0.00534	-0.00706	-0.00244
	(0.10)	(0.09)	(-0.15)	(-0.05)
Abnormal_ Temp	0.641	0.577	0.525	
	(2.34)	(2.08)	(2.12)	
Abnormal_ Temp Quintile 2				-1.046
				(-0.46)
Abnormal_ Temp Quintile 3				0.854
				(0.47)
Abnormal_ Temp Quintile 4				2.683
				(1.38)
Abnormal_ Temp Quintile 5				3.267
				(1.80)
Fixed Effect	None	Year	Month*Year	Month*Year
N	11315	11315	11315	11315
R^2	0.001	0.003	0.031	0.031

Table III. Institutional attention and abnormal temperature

The table reports analyses on the effect of abnormal temperature on institutional attention on high- and low-carbon emission firms. DMR refers to Daily Max Readership and AIA stands for Abnormal Institutional Attention. $AIAC$ is the continuous variable version of AIA. Panel A presents summary statistics. Panel B and C present the result of regressing institutional attention variables on contemporaneous temperature measures: *Average_ Temp*, *Monthly_ Temp*, and *Abnormal_ Temp*, using the sample of high- and low-carbon emission firms, respectively. The regressions also control for one month lagged attention measures and year–month fixed effects. High (low) carbon emission firms are classified as firms in the bottom (top) tercile based on MSIC carbon emission scores within each exchange city. The sample is from 2010 to 2016. Standard errors are clustered by exchange city and by year–month, and the corresponding t-statistics are reported in parentheses.

Panel A: Summary statistics

	Mean	S.D.	P10	P25	P50	P75	P90	Obs
High Emission Firms								
DMR	0.78	0.73	0.00	0.23	0.57	1.14	1.82	40273
AIA	0.14	0.15	0.00	0.05	0.10	0.19	0.33	40273
AIAC	0.28	0.56	-0.35	-0.16	0.10	0.62	1.15	40273
# of unique exchanges	51							
Low Emission Firms								
DMR	0.93	0.77	0.09	0.32	0.73	1.39	2.04	38755
AIA	0.16	0.17	0.00	0.05	0.13	0.23	0.38	38755
AIAC	0.39	0.59	-0.27	-0.10	0.24	0.83	1.29	38755
# of unique exchanges	48							

Panel B: Institutional attention of high emission firms and abnormal temperature

High Emission Firms	(1) DMR	(2) AIA	(3) AIAC	(4) DMR	(5) AIA	(6) AIAC
Average_ Temp	-0.00207	-0.000458	-0.00139	-0.00213	-0.000469	-0.00142
	(-1.13)	(-0.86)	(-1.26)	(-1.16)	(-0.88)	(-1.29)
Monthly_ Temp	-0.000526	-0.000273	-0.000161	-0.000599	-0.000279	-0.000230
	(-1.27)	(-3.73)	(-0.43)	(-1.39)	(-3.49)	(-0.61)
Abnormal_ Temp	0.00324	0.000671	0.00225			
	(3.11)	(2.59)	(3.00)			
Abnormal_ Temp Quintile 2				0.0169	0.00218	0.0163
				(1.15)	(0.64)	(1.49)
Abnormal_ Temp Quintile 3				0.0213	0.00245	0.0190
				(1.69)	(0.86)	(2.11)
Abnormal_ Temp Quintile 4				0.0255	0.00451	0.0180
				(2.40)	(1.90)	(2.37)
Abnormal_ Temp Quintile 5				0.0272	0.00531	0.0197
				(2.32)	(1.79)	(2.44)
Lag DMR	0.680			0.680		
	(46.92)			(46.95)		
Lag AIA		0.457			0.457	
		(28.80)			(28.80)	
Lag AIAC			0.767			0.767
			(56.43)			(56.50)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	40273	40273	40273	40273	40273	40273
R^2	0.495	0.248	0.615	0.495	0.248	0.615

Panel C: Institutional attention of low emission firms and abnormal temperature

Low Emission Firms	(1) DMR	(2) AIA	(3) AIAC	(4) DMR	(5) AIA	(6) AIAC
Average_ Temp	-0.00294	-0.000826	-0.00180	-0.00292	-0.000816	-0.00180
	(-1.49)	(-1.60)	(-1.43)	(-1.47)	(-1.51)	(-1.41)
Monthly_ Temp	0.000397	0.000175	0.000175	0.000388	0.000176	0.000168
	(1.12)	(1.45)	(0.62)	(0.84)	(1.04)	(0.42)
Abnormal_ Temp	0.0000878	-0.000288	0.000159			
	(0.05)	(-0.56)	(0.14)			
Abnormal_ Temp Quintile 2				0.0206	0.00376	0.0136
				(2.16)	(1.18)	(2.49)
Abnormal_ Temp Quintile 3				0.0153	0.00110	0.0128
				(1.34)	(0.31)	(2.00)
Abnormal_ Temp Quintile 4				0.0122	0.00112	0.00882
				(0.81)	(0.27)	(0.92)
Abnormal_ Temp Quintile 5				0.0165	0.000900	0.0129
				(1.03)	(0.18)	(1.41)
Lag DMR	0.686			0.686		
	(49.36)			(49.11)		
Lag AIA		0.476			0.476	
		(30.13)			(29.96)	
Lag AIAC			0.768			0.768
			(63.79)			(63.55)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	38755	38755	38755	38755	38755	38755
R^2	0.506	0.273	0.619	0.506	0.273	0.619

Table IV. Stock return and abnormal temperature

The table reports analyses on the effect of abnormal temperature on returns of high- and low-carbon emission firms. High (low) carbon emission firms are classified as firms in the bottom (top) tercile based on MSIC carbon emission scores within each exchange city. $Adjusted\ Ret_t$ is the stock's return in month t minus the average return of stocks in the same size quintile by each exchange city. $Adjusted\ Ret_{t+1,t+3}$ and $Adjusted\ Ret_{t+1,t+6}$ are cumulative adjusted return over months $t+1$ to $t+3$ and $t+1$ to $t+6$, respectively. Panel A presents summary statistics. Panel B reports the result of regressing $Adjusted\ Ret_t$ on contemporaneous temperature measures: *Average_ Temp*, *Monthly_ Temp*, *Abnormal_ Temp*, and *Abnormal_ Temp* quintile dummies. Year–month fixed effects are also included. The sample is from 2008 to 2016. Standard errors are clustered by exchange city and by year–month, and the corresponding t-statistics are reported in parentheses.

Panel A: Summary statistics

	Mean	S.D.	P10	P25	P50	P75	P90	Obs
High Emission Firms								
$Adjusted\ Ret_t$	-0.23	10.91	-11.73	-5.66	-0.46	4.76	10.91	37888
$Adjusted\ Ret_{t+1,t+3}$	-1.18	19.07	-22.30	-11.05	-1.41	7.93	18.44	37888
$Adjusted\ Ret_{t+1,t+6}$	-1.62	28.44	-32.65	-16.37	-2.44	11.20	26.87	37888
# of unique exchanges	62							
Low Emission Firms								
$Adjusted\ Ret_t$	0.14	8.03	-8.49	-4.15	-0.06	4.19	8.82	33515
$Adjusted\ Ret_{t+1,t+3}$	0.33	14.11	-15.15	-7.48	-0.01	7.66	15.71	33515
$Adjusted\ Ret_{t+1,t+6}$	0.51	20.80	-21.82	-11.04	-0.28	10.96	22.47	33515
# of unique exchanges	55							

Panel B: Regression of adjusted returns on abnormal temperature

	High Emission Firms		**Low Emission Firms**	
Dep.Var.: *Adjusted* Ret_t	(1)	(2)	(3)	(4)
Average_ Temp	-0.000851	0.000276	-0.00198	-0.00114
	(-0.07)	(0.02)	(-0.26)	(-0.14)
Monthly_ Temp	-0.0142	-0.0137	0.00562	0.00671
	(-0.86)	(-0.80)	(0.51)	(0.61)
Abnormal_ Temp	-0.0911		0.00482	
	(-2.63)		(0.24)	
Abnormal_ Temp Quintile 2		-0.336		0.144
		(-1.25)		(0.95)
Abnormal_ Temp Quintile 3		-0.541		-0.232
		(-1.62)		(-1.91)
Abnormal_ Temp Quintile 4		-0.630		-0.105
		(-2.16)		(-0.65)
Abnormal_ Temp Quintile 5		-0.850		0.108
		(-2.75)		(0.50)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes
N	37888	37888	33515	33515
R^2	0.044	0.044	0.011	0.012

Table V. Emission-minus-clean portfolio return and abnormal temperature

Stocks are sorted into high- and low-carbon emission portfolios based on the most recent year-end MSCI carbon emission scores by each exchange city. The high-carbon emission portfolio, labeled as $EMISSION$ includes stocks with carbon emission score lower than the bottom tercile. The low-carbon emission portfolio, labeled as $CLEAN$ includes stocks with carbon emission score higher than the top tercile. Portfolio return (in percent) equals the average adjusted return of stocks, equal weighted (EW) or value weighted (VW). Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. EMC equals $EMISSION$ minus $CLEAN$. $EMC_{t+1,t+3}$ and $EMC_{t+1,t+6}$ are calculated using adjusted returns over months $t+1$ to $t+3$ and $t+1$ to $t+6$, respectively. Panel A reports summary statistics. Panel B reports the result of regressions of EMC on contemporaneous temperature variables, while Panel C reports the result of regressing $EMISSION(EW)$ and $CLEAN(EW)$ portfolio returns on temperature variables. The sample is from 2008/01 to 2016/06. Standard errors are clustered by exchange city and year–month, and the corresponding t-statistics are reported in parentheses.

Panel A: Summary statistics

	Mean	S.D.	P10	P25	P50	P75	P90	N
$EMC(EW)_t$	-0.43	4.55	-5.39	-2.48	-0.34	1.77	4.60	704
$EMC(VW)_t$	-0.31	4.49	-5.09	-2.46	-0.28	2.21	4.11	704
$EMISSION(EW)_t$	-0.30	3.59	-4.52	-2.12	-0.28	1.34	3.44	704
$CLEAN(EW)_t$	0.13	3.05	-2.79	-1.38	0.11	1.42	3.42	704
$EMC(EW)_{t+1,t+3}$	-1.20	8.59	-10.78	-5.49	-0.88	3.26	7.61	704
$EMC(EW)_{t+1,t+6}$	-1.97	12.48	-15.57	-8.44	-1.25	4.71	11.69	704
$Average\_Temp_t$	59.11	10.34	47.32	52.34	55.03	64.03	73.82	704
$Monthly\_Temp_t$	0.26	11.31	-14.58	-8.49	0.28	8.79	14.54	704
$Abnormal\_Temp_t$	0.17	2.96	-3.33	-1.40	0.15	1.73	3.63	704
# of unique exchanges	19							

Panel B: Regression of *EMISSION* and *CLEAN* portfolio returns on abnormal temperature

	Equal Weighted		Value Weighted	
Dep. Var.: *EMC*	(1)	(2)	(3)	(4)
Average_ Temp	-0.000138	0.00203	0.00547	0.00629
	(-0.01)	(0.09)	(0.21)	(0.25)
Monthly_ Temp	-0.0512	-0.0544	-0.00399	-0.00748
	(-1.28)	(-1.34)	(-0.14)	(-0.27)
Abnormal_ Temp	-0.158		-0.0911	
	(-2.55)		(-1.78)	
Abnormal_ Temp Quintile 2		-0.148		0.0628
		(-0.32)		(0.14)
Abnormal_ Temp Quintile 3		-0.420		-0.152
		(-0.82)		(-0.32)
Abnormal_ Temp Quintile 4		-0.103		0.289
		(-0.17)		(0.66)
Abnormal_ Temp Quintile 5		-1.810		-1.455
		(-2.24)		(-2.05)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes
N	704	704	704	704
R^2	0.279	0.284	0.223	0.231

Panel C: Regression of *EMC* returns on abnormal temperature

	(1)	(2)	(3)	(4)
Dep. Var.: *Portfolio Return(EW)*	EMISSION	CLEAN	EMISSION	CLEAN
Average_ Temp	-0.00231	-0.00218	0.00113	-0.000908
	(-0.13)	(-0.20)	(0.07)	(-0.08)
Monthly_ Temp	-0.0322	0.0189	-0.0327	0.0217
	(-1.41)	(0.86)	(-1.39)	(1.00)
Abnormal_ Temp	-0.142	0.0162		
	(-2.58)	(0.39)		
Abnormal_ Temp Quintile 2			0.142	0.290
			(0.44)	(0.75)
Abnormal_ Temp Quintile 3			-0.456	-0.0361
			(-1.12)	(-0.10)
Abnormal_ Temp Quintile 4			-0.385	-0.282
			(-0.86)	(-0.71)
Abnormal_ Temp Quintile 5			-1.223	0.586
			(-2.31)	(1.23)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes
N	704	704	704	704
R^2	0.359	0.197	0.360	0.204

Table VI. Long-term stock return subsequent to abnormal temperature

The table presents the analyses of long-term return of high-carbon emission firms subsequent to abnormal temperature. In Panel A, $Adjusted\ Ret_{t+1,t+3}$ and $Adjusted\ Ret_{t+1,t+6}$ are regressed on temperature variables at month t. In Panel B, the dependent variables are equal-weighted $EMC_{t+1,t+3}$ and $EMC_{t+1,t+6}$. In both panels, the sample is from 2008 to 2016. Standard errors are clustered by exchange city and year–month, and the corresponding t-statistics are reported in parentheses.

Panel A: Stock-level return

	(1)	(2)	(3)	(4)
Dep. Var.: *Adjusted Ret*	$t+1$ to $t+3$	$t+1$ to $t+6$	$t+1$ to $t+3$	$t+1$ to $t+6$
Average_ Temp	0.0234	0.0452	0.0231	0.0443
	(0.93)	(1.01)	(0.93)	(0.99)
Monthly_ Temp	-0.0624	-0.0384	-0.0600	-0.0361
	(-1.62)	(-0.78)	(-1.56)	(-0.74)
Abnormal_ Temp	-0.00087	0.0655		
	(-0.02)	(0.74)		
Abnormal_ Temp Quintile 2			-0.329	-0.717
			(-0.62)	(-1.17)
Abnormal_ Temp Quintile 3			-0.457	-0.499
			(-0.91)	(-0.69)
Abnormal_ Temp Quintile 4			-0.372	-0.428
			(-0.91)	(-0.55)
Abnormal_ Temp Quintile 5			0.116	0.105
			(0.26)	(0.14)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes
N	37888	37888	37888	37888
R^2	0.044	0.048	0.044	0.048

Panel B: *EMC* portfolio return

	(1)	(2)	(3)	(4)
Dep. Var.: $EMC(EW)$	$t+1$ to $t+3$	$t+1$ to $t+6$	$t+1$ to $t+3$	$t+1$ to $t+6$
Average_ Temp	0.0434	0.0665	0.0448	0.0641
	(1.12)	(0.87)	(1.15)	(0.85)
Monthly_ Temp	-0.125	-0.0985	-0.124	-0.0987
	(-1.36)	(-0.64)	(-1.33)	(-0.64)
Abnormal_ Temp	0.0151	0.234		
	(0.14)	(1.13)		
Abnormal_ Temp Quintile 2			-0.627	-1.049
			(-0.48)	(-0.65)
Abnormal_ Temp Quintile 3			-0.948	-1.019
			(-1.19)	(-0.98)
Abnormal_ Temp Quintile 4			-0.550	-0.137
			(-0.60)	(-0.11)
Abnormal_ Temp Quintile 5			-0.664	-0.262
			(-0.57)	(-0.20)
Month*Year Fixed Effect	Yes	Yes	Yes	Yes
N	704	704	704	704
R^2	0.296	0.352	0.297	0.351