Attention to Global Warming*

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July 2019

Abstract

We find that people revise their beliefs about climate change upward when experiencing warmer than usual temperatures in their area. Using international data, we show that attention to climate change, as proxied by Google search volume, increases 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. Retail investors (not institutional investors) sell carbon-intensive firms in such weather, and return patterns are unlikely to be driven by changes in fundamentals. Our study sheds light on peoples' collective beliefs and actions about global warming. (*JEL* D83, G12, G14, G15, Q54)

*We thank Andrew Karolyi (the Editor), Vikas Agarwal, Laura Bakkensen, Zhi Da, Andrew Ellul, Harrison Hong, Roger Loh, Pedro Matos, Abhiroop Mukherjee, Adriaan Perrels, Jose Scheinkman, Wing Wah Tham, Bohui Zhang, and Dexin Zhou; three anonymous referees; and seminar participants at the 2nd International Conference on Econometrics and Statistics (EcoSta), 8th Helsinki Finance Summit on Investor Behavior, 10th Annual Volatility Institute Conference: A Financial Approach to Climate Risk, Asian Bureau of Finance and Economic Research (ABFER) 6th Annual Conference, China International Conference in Finance 2018, Review of Financial Studies Climate Finance Workshop 2017 and Climate Finance Conference 2018, Society for Financial Studies (SFS) Cavalcade Asia-Pacific 2018, Cheung Kong Graduate School of Business, Chinese University of Hong Kong, Hong Kong Baptist University, Hong Kong Polytechnic University, Renmin University of China, and University of Melbourne for helpful comments. Jingxuan Chen, Haojun Xie, and Hulai Zhang provided excellent research assistance. We acknowledge the General Research Fund of the Research Grants Council of Hong Kong (Project Number: 16516616) for financial support.

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Introduction

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

Pierre-Louis (2017) of the *The New York Times* wrote in response "But Mr. Trump's tweet made the common mistake of looking at local weather and making broader assumptions about the climate at large." This misunderstanding about climate change is indeed a common mistake. Global warming is a long-term trend usually not visible on a personal level. In contrast, the local temperature in a given month or year is more noticeable, even though it can be caused by reasons unrelated to global warming, for example, ocean oscillations, such as the El Niño Southern Oscillation, ENSO (Intergovernmental Panel on Climate Change, IPCC 2014; Schmidt, Shindell, and Tsigaridis 2014). For example, a record-breaking warm month of July in New York City provides negligible information about the increase in the average global temperature in the following decade, but the local temperature in July is much more visible to New Yorkers than the 10-year global trend.

In this paper, we test how people react to abnormal local temperatures by examining their attention to climate change and stock prices. Our data cover seventy-four cities in the world with major stock exchanges. The advantage of using international attention and financial data is that we can estimate people's opinions in different parts of the world at a high frequency (unlike surveys) and study their follow-up actions, as investors trade on their beliefs and move stock prices. Humans' collective belief and effort are important determinants of the efficacy of climate policies and campaigns. Our study aims to empirically identify how the general public realizes and responds to the impacts of global warming.

Because their attention is limited, people are likely to focus on attention-grabbing weather events and personal experiences. The local weather conditions are people's first-hand experience. The impact of local weather also can be amplified through communication channels and the media (media attention to climate change appears to be higher in the record-breaking warmest years than in nonrecord years) (Schmidt 2015). Extreme local temperatures 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 abnormally warm weather. The second set of analyses examines whether this experience affects financial markets; because of the home bias (see, e.g., the review by Karolyi and Stulz 2003), the prices of local stocks are affected by local investors' trading behavior.

Our results show that during abnormally warm months in a particular city, the volume of Google searches for the topic of "global warming" in that city increases.[1] Our analysis controls for time fixed effects, and therefore the relationship originates from geographical variation. Not all parts of the world are equally warm in a given month; people tend to seek more information about global warming if they live in cities that have relatively higher abnormal temperatures than other cities in that month. This effect is the most prominent when the local abnormal temperature is in the city's top quintile, as this weather experience is more salient.

If investors revise their beliefs about global warming, they may buy stocks with lower climate sensitivities and sell stocks with higher climate sensitivities such that the former

[1] In this paper, we use the term "abnormally warm" to refer to cases in which a city's temperature is significantly higher than the historical average temperature at the same point in the year. Our Google data capture the search activity in each city and cover different languages. See Section 1 for a list of papers that study the Google search volume of global warming in the United States.

outperform the latter. We sort stocks into those with high and low sensitivities using proxies for greenhouse gas emission levels. Firms are classified as high-emission firms if they belong to industries that the IPCC identifies as major emission sources. These companies tend to be more sensitive to climate change if their future cashflows are adversely affected by higher production costs and tighter environmental regulations or if socially responsible investors avoid holding their stocks.

We find evidence that carbon-intensive firms earn lower stock returns than other firms when the local exchange city is abnormally warmer in that month. The effect is again more prominent when the abnormal temperature is in the city's top quintile. An increase in the city's abnormal temperature from the coolest quintile to the warmest quintile is associated with a reduction of 48 bps in the long-short emission-minus-clean portfolio. In an alternative specification, we define high- and low-emission firms according to their MSCI Carbon Emission Scores, which capture individual companies' emission levels relative to their industry peers, and achieve similar results. We do not find any significant return reversal in the longer term (up to a year). The return patterns are observed in both energy and nonenergy high-emission sectors and are robust to size adjustments. Furthermore, we do not obtain the same results in a "placebo" test that uses an earlier sample period, 1983–2000, when global warming was less of an issue.

To better understand the mechanism through which temperature affects prices, we examine proxies for different investors' trading behavior.[2] We focus on local blockholders, local institutional investors, and retail investors (the majority of which are local) because they are exposed to the same temperature. Which of these investors decrease their holdings of high-emission firms in an abnormally warm quarter? Consistent with our conjecture that individuals are more prone to limited attention and drawn to notable events, we find evidence that retail investors sell high-emission firms and buy low-emission firms. Institutional

[2] Data on the quarterly equity positions of blockholders (who hold 5% or more of the total number of shares) and of institutional investors who hold less than 5% of total shares are obtained from DataStream and FactSet, respectively. The complement of these holdings gives us an estimate of retail investors' positions.

investors (local and foreign) do not respond systematically to abnormal temperatures. More interestingly, we find that local blockholders trade in the opposite direction of retail investors. Therefore, local abnormal temperatures do not appear to adversely affect all carbon-intensive firms' operations in a fundamental manner, as blockholders of these firms are generally buying shares and household investors should be less informed than blockholders.[3] We conclude that unusually warm weather is a salient event that affects individual investors, and we run a series of tests and find no evidence that the price impact is a result of belief updates about firms' future cashflows. Rather, people seem to avoid holding high-emission firms as they become more aware of climate risk, similar in spirit to avoiding "sin" stocks (companies involved in producing alcohol, tobacco, and gaming).

Recent literature on climate change also examines people's beliefs and personal experience. Zaval et al. (2014), Akerlof et al. (2013), and Myers et al. (2012) show that personal experience with global warming, as reported in surveys, leads to an increased perception of climate risk in the United States; this finding is confirmed by Broomell, Budescu, and Por (2015) and Howe et al. (2013) using international surveys. Konisky, Hughes, and Kaylor (2016), Borick and Rabe (2014), and Joireman, Truelove, and Duell (2010) find a similar relationship using objective measures of 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 also are followed by actions: participants are more likely to donate their earnings to a global warming charity. Surveys measure beliefs about global warming in all these studies. 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 and trading behavior. Our findings are related to experiential learning, in which people begin the learning process based on con-

[3]Although we cannot rule out the possibility that local blockholders revise their beliefs about global warning downward in an abnormally warm quarter (which would be puzzling), our preferred interpretation is that these blockholders respond to the decrease in stock prices, similar to the model developed by Hong, Wang, and Yu (2008). Hong, Wang, and Yu (2008) argue that firms are buyers of last resort for their own stocks. They repurchase shares when prices drop below their fundamental value.

crete experience and form abstract concepts by observing and analyzing information before acting (Boud, Keogh, and Walker 1985; Kolb 1984). In our context, we can see whether people read more about global warming (on the Internet) after they are personally affected by the local weather.

This paper complements previous empirical findings on reactions to climate and other external conditions. Chang, Huang, and Wang (2018) find that more health insurance contracts are sold when the air is polluted, but they are more likely to be canceled if air quality improves shortly afterward. Busse et al. (2015) and Conlin, O'Donoghue, and 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 (2019) document underreaction of food companies' stock prices to trends in droughts that are exacerbated by global warming. Using a comprehensive database of coastal home sales in the United States, Murfin and Spiegel (forthcoming) find that real estate prices do not factor in the risk of sea level rise. Our results are also in line with general underreaction to global warming. Finally, the finding that people pay more attention and our observation of 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 (Goetzmann et al. 2015; Kamstra, Kramer, and Levi 2003, among others).

1 Methods and Hypotheses

We would like to identify investor reaction to global warming in times of unusually warm local weather. Given that climate change is a global phenomenon, we conduct our study in a broad international setting to understand people's collective beliefs and reactions. The international setting also gives us an identification advantage: climate science research shows that extreme temperatures rarely occur simultaneously in both the Northern and Southern Hemispheres (see, e.g., Neukom et al. 2014).

The reaction is first measured by the monthly Google Search Volume Index (SVI) of the topic "global warming" in a city, which proxies for people's attention. Google offers SVI for topics and search terms. We use topics instead of search terms because the former addresses misspellings and searches in different languages, as Google's algorithms can group different searches that have the same meaning under a single topic.[4] Our idea follows Da, Engelberg, and Gao (2011), who use SVI of tickers to study investor attention. Several other papers also examine Google search volume for global warming and climate change and relate it to local weather conditions: e.g., Lineman et al. (2015), Cavanagh et al. (2014), Herrnstadt and Muehlegger (2014), Lang (2014), and Kahn and Kotchen (2011). These studies focus on U.S. data, whereas our paper covers more than seventy cities worldwide and many different languages.

To understand the learning process, we decompose local temperatures into three components, which account for predictable, seasonal, and abnormal patterns. Specifically, for each city i in month t, we calculate the monthly $Temperature_{it}$ by taking the average of daily average temperatures in our data. Then we define

$$Temperature_{it} = Aver\_Temp_{it} + Mon\_Temp_{it} + Ab\_Temp_{it}, \tag{1}$$

where $Aver\_Temp_{it}$ is the average monthly local temperature in city i over the 120 months prior to t; Mon_Temp_{it} is the average deviation of this month's temperature from the average, that is, the average temperature in city i in the same calendar month over the last 10 years minus $Aver\_Temp_{it}$; and Ab_Temp_{it} is the remainder. Our focus is how local abnormal temperatures affect changes in attention (as proxied by the change in SVI, adjusted for seasonality). Even though a city's monthly Ab_Temp provides little fundamental information about the future global climate, it represents new experience and is a salient event for people in the city.

[4]See the official Google Search blog for details: `https://search.googleblog.com/2013/12/an-easier-way-to-explore-topics-and.html`.

Then we turn to investor reaction in the stock market. We study monthly size-adjusted stock returns under abnormally warm weather in the exchange city. The size-adjusted return is defined as the stock return minus the average return of stocks in the same size quintile in the exchange in the same month. Exchange cities are important cities in which many investors are located, and prices are affected by domestic investors (see, e.g., Chan, Hameed, and Lau 2003).[5] We examine the cross-section of firms with different sensitivities to climate change. If investors begin 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. The short-term and the long-term patterns are examined. Without reversal or some continuation in the long run, it is consistent with belief updating. A reversal indicates that the short-term price changes overshoot and investors overreact.

The effect of abnormally warm weather on stock prices can occur through multiple channels. First, climate-unfriendly firms may be fundamentally damaged. Second, people may update their own valuation of firms when they revise their beliefs about climate change upward. Investors may think that high-emission firms' future cashflows are adversely affected because climate change can hurt firms' production functions, impose higher costs for future emissions, or induce tighter regulations on emissions. Third, and finally, on recognizing the risk of global warming, socially responsible investors may stay away from firms that are climate unfriendly, similar to the way in which "sin" stocks are shunned by some investors (Hong and Kacperczyk 2009). Sections 3.4 and 3.5 present a series of tests to distinguish between these channels.

[5]In large countries, such as China, India, Russia, and the United States, population (and therefore local investors) are more dispersed, and the exchange city's temperature is a weaker proxy for the effect of weather on investors. Table 5 shows a weaker relationship between the exchange city's abnormal temperature and returns in the ten largest countries in our sample.

2 Data

In the following, we describe the various databases we use, as well as the variables we obtain and examine in our analyses (the databases used in the Internet Appendix are described there).

2.1 Weather

We obtain daily weather data from the Global Surface Summary of Day Data, which are 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 since 1973 (the coverage was considerably lower before 1973). The weather conditions include temperature, wind speed, cloudiness, precipitation, snow depth, etc. By identifying the location coordinates, we select the closest weather station to the address of the exchange. We collect the daily records of seventy-four cities with major stock exchanges from 1973 to 2017. Our main test period is from 2001 to 2017, when climate change is a global phenomenon.[6] As noted in Section 2, abnormal temperatures require 10 years of data to calculate. We use the period from 1983 to 2000, when few people recognized climate change, to conduct a "placebo" test.

2.2 Google Search Volume Index

The data source for internet search activity is Google Trends, which provides a Search Volume Index (SVI) of the search topic of "global warming." We download the monthly

[6] Our conclusion remains the same if we use other similar test periods in the twenty-first century. Climate change became a global concern in the early twenty-first century. For example, in its Third Assessment Report released in 2001, the IPCC claims that "there is new and stronger evidence that most of the observed warming of the past 50 years is attributable to human activities" (https://archive.ipcc.ch/graphics/speeches/robert-watson-november-2001.pdf). In 2001, national science academies of many different countries issued a joint statement stating that "IPCC represents the consensus of the international scientific community on climate change science" (*Science* 2001).

SVI in each of the seventy-four locations from 2004 (when Google Trends began to provide data) to 2017. We examine search activity at both the city and country levels (except for some small countries for which the search volume data are available only at the country level).[7]

2.3 Stock and company information

Stock returns, market capitalization, and industry information are available from Thomson Reuters DataStream. For U.S. stocks, we use return and market capitalization data from CRSP (we obtain a list of U.S. stocks from DataStream and match them to CRSP using ISIN and CUSIP). DataStream covers more than 100,000 equities in nearly 200 countries from 1980 onward. We can observe the firms' countries of domicile (from the NATION variable) and their exchange cities, but not the locations of firms' establishments. The literature notes that DataStream may suffer from data errors. We winsorize raw returns at the top and bottom 2.5% in each exchange in each month. Following Hou, Karolyi, and Kho (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 (DataStream repeats the last valid data point for delisted firms).

2.4 Stock ownership

DataStream provides the aggregate ownership in a stock by domestic and foreign blockholders (who hold more than 5% of shares outstanding) in every quarter. Quarterly holdings by institutional investors and their locations (at the country level) are obtained from FactSet, which covers 33 of our 74 exchange cities. We use the SAS code provided by Ferreira and

[7] We also download the monthly SVI for the topic "climate change," but the search traffic for this topic is much lower than that of "global warming" in the first few years of our sample period. In more recent years, the SVIs of the two topics are highly correlated. In the paper, we report the results using the SVI of "global warming."

Matos (2008), available on WRDS, to calculate the ownership by institutional investors, excluding blockholders. Then we define retail ownership as (100% − DataStream blockholders' ownership − FactSet institutional ownership excluding blockholders).[8]

2.5 Carbon emission

We identify high-emission firms in two ways. First, we adopt the industry definitions provided by the Intergovernmental Panel on Climate Change (IPCC), the leading international body for the assessment of climate change. Five major industry sectors are identified as major emission sources: Energy; Transport; Buildings; Industry (such as chemicals and metals); and Agriculture, Forestry, and Other Land Use (AFOLU). Each sector is further divided into subcategories (Krey et al. 2014 offers a full list). We hand-match the IPCC subcategories with the industry names provided by DataStream.[9] All firms in the matched industries are classified as high-emission firms.

Second, we obtain firms' carbon emission estimates from MSCI ESG Ratings, which analyzes companies' environmental, social, and governance issues. Specifically, MSCI ESG studies greenhouse gas (GHG) emissions of companies worldwide. A Carbon Emission Score is given to each firm annually since 2007, on a scale of 0–10. Companies with better performance on this issue score higher. The score is adjusted by industry and is thus comparable for two firms from different industries. We define high- (low-) carbon emission firms as firms whose MSCI Carbon Emission Scores in the previous calendar year are lower than 3 (higher than 7).

The two definitions identify high-emission firms differently. For example, Toyota Motor

[8] In other words, we do not directly measure retail ownership, and the proxy is subject to measurement errors. Several other papers also define the complement of U.S. institutional holdings as a proxy for individual U.S. investors' demand: for example, DeVault, Sias, and Starks (2019), Agarwal, Vashishtha, and Venkatachalam (2018), Malmendier and Shanthikumar (2007), Griffin, Harris, and Topaloglu (2003), and Cohen, Gompers, and Vuolteenaho (2002).

[9] For example, Coal (DataStream Industry Classification Benchmark ICB code = 1771), Gold Mining (DataStream ICB code = 1777), and General Mining (DataStream ICB code = 1775) are matched with Mining and Quarrying (IPCC code = 1A2f4). Table IA.1 in the Internet Appendix provides the map.

Corporation, listed on the Tokyo Stock Exchange, belongs to the Automobiles industry in DataStream (which is mapped to the Transport Equipment industry, IPCC code = 1A2f2). According to the first method, it is classified as a high-emission firm. The average MSCI score of Toyota Motor Corporation in our sample period is 9.4, and the second method places it in the low-emission group in all years. One can interpret that the company is a relatively clean firm in a high-emission industry. Throughout the paper, we primarily use IPCC definitions because they are available for all firms and for a longer period. MSCI covers only a subset of firms in a small number of exchanges. It may have a selection issue and the results should be interpreted with caution.[10]

2.6 Price of carbon and environmental regulatory regime index

The price of carbon is measured by carbon futures prices. EUA Futures Contracts, traded on the Intercontinental Exchange (ICE) Futures Europe, are contracts in which the traders are obliged to make or take the delivery of 1,000 emission allowances. Each allowance is an entitlement to emit one ton of carbon-dioxide-equivalent gas. We download the data from Bloomberg (symbol: MO1 Comdty), beginning in April 2005. We also use the environmental regulatory regime index developed by Esty and Porter (2001). The index is a ranking of countries' regulatory stringency, structure, subsidies, and enforcement; it represents the quality of the environmental regulatory system.

[10]MSCI collects data once a year from the most recent corporate resources, such as annual reports and corporate social responsibility reports. When direct disclosure is not available, MSCI uses GHG data reported by the Carbon Disclosure Project or government databases. Note that MSCI does not assign a score to every public firm. The number of firms with a valid MSCI Carbon Emission Score in our data increases from 1,888 in 2007 to 11,239 in 2017, as shown in Table IA.2 in the Internet Appendix. Although MSCI also issues other climate-change-related scores to companies, such as the Climate Change Theme Score, the Carbon Emission Score is available for the longest period.

3 Empirical Results

Our tests aim to investigate two questions: (1) whether people's attention varies with local temperatures and (2) if so, how experiences of local temperatures affect the stock price of local firms and investors' trading behavior. Table 1 shows the list of 74 stock exchange cities. It reports the number of unique stocks, number of foreign firms (whose country of domicile information is available and is different from that of the exchange city), number of emission firms and foreign emission firms (defined using the IPCC classification), as well as average retail and blockholder ownerships in each city in our sample. In all regressions below, all standard errors are clustered by exchange city and year-month (or year-quarter for regressions of changes in ownership).

3.1 Attention and local temperatures

To capture changes in attention, we first calculate the log monthly change in the Google Search Volume Index, $DSVI$. $DSVI_{it}$ is the log change in SVI in city i in month t, adjusted for seasonality.[11] Panel A of Table 2 shows the summary statistics of $DSVI_{it}$, as well as those of $Aver\_Temp_{it}$, Mon_Temp_{it}, and Ab_Temp_{it}, the decomposition of temperature in city i in month t according to Equation (1). The mean $DSVI$ is close to zero (-0.02%), whereas the mean $Aver\_Temp$, Mon_Temp, and Ab_Temp are 61.9°F, 0.16°F, and 0.27°F, respectively.

Then we run the following regression:

$$DSVI_{it} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it}, \tag{2}$$

[11] $DSVI$ is defined as the residuals from the regression of the log change in the 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 Shanghai, are dropped from the analysis, because Google Trends returns no valid local data for them. Table IA.3 in the Internet Appendix examines changes in attention at daily, weekly, and quarterly levels. The results are weaker. A day or week of abnormal temperatures may not shift beliefs, whereas a month is more likely to. It may also take an extended period of warm weather for the media effect to come into play. (At the quarterly level, the results are also weaker, but the average extreme temperature within a quarter is attenuated.)

Our coefficient of interest is β_1. Table 2, panel B, reports the results. In Column 1, the coefficient estimate of Ab_Temp is significantly positive (t-stat = 2.3), which suggests that people pay more attention to global warming when they are experiencing an abnormally high temperature. The regression includes year-month fixed effects, meaning that the relationship is observed from the geographic variation (in a given month, when a city is abnormally warm relative to other places, people in that city tend to search about global warming more than people in other places).

In Column 2, we rank all months into quintiles based on Ab_Temp_{it} in city i and use these quintile dummies in the regression instead of Ab_Temp. The coefficients of the quintile dummies indicate that the temperature effect is nonlinear: the coefficients of quintiles 2, 3, and 4 are not significantly different from zero, while the coefficient of quintile 5 is 4.84 (t-stat = 2.6). 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.

The economic magnitude is worth noting. Based on the estimation in Column 2, compared to the 20% abnormally coolest months, in the 20% abnormally warmest months people search more about global warming by 4.8%, or about 7.3% of its standard deviation (which is 66.5%, as shown in panel A).

Finally, we repeat all the regressions by replacing SVI in city i with SVI in the country (for countries with more than one stock exchange, we pick the exchange city with the largest total market capitalization; the regressions include sixty-three countries). Panel A of Table 2 shows that the summary statistics of the two SVIs are similar. Columns 3 and 4 report the regression results, which are qualitatively similar to those at the city level. In later tests, we have only country-level information on investor locations. Most exchange cities are important cities with high populations, concentrated capital, and extensive media coverage.

Because abnormal temperature in the exchange city is strongly associated with people's attention at the country level, it seems reasonable to use the city's temperature to proxy for people's experience in the country.

The Internet Appendix examines whether institutional investor and media attention also change with local abnormal temperatures. We follow Ben-Rephael, Da, and Israelsen (2017) to measure abnormal institutional investor attention (AIA). AIA tracks how frequently Bloomberg users, who are likely financial institutions, search and read information about a certain stock. While we do not have users' location, we can obtain information at the stock level (in 45 exchanges). Table IA.4 shows the results. We do not find evidence that abnormally warm weather leads to different levels of institutional attention to high-emission and low-emission firms in the exchange. This finding is in line with our trading results in Section 3.5 and our hypothesis that local weather mostly affects retail investors. Using data from Raven Pack News Analytics, Table IA.5 finds that media attention to high-emission firms do not vary with local abnormal temperatures. However, most data from Raven Pack News come from English-speaking media (which may not be located in the exchange city) and are available at the stock level (so that generic stories about climate change will not be captured). Future research can revisit these questions if there are better measures of international institutional investor and media attention.

3.2 Stock returns and local temperatures

Next, we examine whether local weather affects stock prices, focusing on the differential reactions in the cross-section of firms. We first form two portfolios according to the IPCC definitions described in Section 2. In each city i from 2001 to 2017, portfolio $EMISSION_i$ includes all firms whose DataStream industry group is mapped with the IPCC sectors. All remaining firms in city i are assigned to portfolio $CLEAN_i$. A long-short portfolio EMC_i (which stands for Emission Minus Clean) is formed by buying $EMISSION_i$ and selling $CLEAN_i$. We construct all portfolios using equal weights and value weights. Panel A of

Table 3 shows the summary statistics. Size-adjusted returns are reported.[12] Figure 1 plots the average equal-weighted EMC size-adjusted returns and the confidence intervals across five temperature quintiles in the exchange city. We see a general decrease in EMC returns as we move up the temperature quintiles, with statistically significant underperformance in the warmest quintile. Summary statistics for raw returns (not adjusted for size) and longer-term returns (up to 12 months) of EMC are also shown in panel A.

Similar in spirit to Hirshleifer and Shumway (2003) and Saunders (1993), who examine the relationship between morning sunshine in a city and index returns, we capture investors' experience by using local abnormal temperature in the city. We run the following regression:

$$EMC_{it} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it}, \tag{3}$$

where EMC_{it} is the value-weighted or equal-weighted, size-adjusted or raw return of the EMC portfolio in city i in month t (from 2001 to 2017), and Ab_Temp_{it} is the abnormal temperature in city i in month t based on the decomposition in Equation (1). Year-month fixed effects are included.[13]

Panels B (equal-weighted) and C (value-weighted) of Table 3 offer the results. Column 1 of Panel B shows that higher abnormal temperature is associated with significantly lower EMC size-adjusted returns. A 1-standard-deviation increase in Ab_Temp corresponds to a decrease of 16 bps in EMC return ($= -0.060 \times 2.676$). Column 2 replaces Ab_Temp with the quintile dummies based on the city's abnormal temperature. It shows that the negative effect on EMC returns is the strongest in the highest temperature quintile, consistent with

[12] We use size-adjusted returns, because the market capitalization data obtained from DataStream have better coverage than other financial data. Other models can calculate adjusted returns (e.g., a factor model 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. Specifically, we check the availability of the following variables in the Worldscope database: book/market, dividend/price, earnings/price, and long-term debt/common equity. Requiring at least one of these variables will reduce the number of observations in our main regression by 81%. Twelve of our seventy-four exchange cities have zero observations, and fifty-eight cities have less than 10% of the observations remaining.

[13] Table IA.6 in the Internet Appendix runs these regressions at weekly and quarterly levels. We obtain similar results that are statistically weaker.

our Google SVI results in Section 3.1. The economic impact is sizeable, with a change from temperature quintile 1 (coolest) to quintile 5 (warmest) corresponding to a drop of 48 bps (t-stat $= -4.0$) in size-adjusted return. The results are similar when we consider raw returns (Columns 3 and 4). Finally, Columns 5 and 6 study $EMISSION$ and $CLEAN$ portfolio size-adjusted returns, respectively. Relative to the city's coldest temperature quintile, $EMISSION$ ($CLEAN$) earns significantly lower (higher) returns in the warmest quintile, at the 1% significance level. Therefore, both portfolios contribute to the low EMC returns in the warmest months. The results using value-weighted returns are generally similar, as shown in panel C.

Next, we examine the long-term performance subsequent to an abnormally warm month:

$$EMC_{i,t+1,t+n} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it}, \tag{4}$$

where $n = \{3, 6, 12\}$ and the returns are measured from month $t+1$ to month $t+n$. Year-month fixed effects are included. If β_1 is negative or zero, it is consistent with slow belief updating; investors with limited attention generally overlook climate risk but recognize it when reacting to attention-grabbing weather events. Otherwise, if β_1 appears to be positive, it implies that part of the belief update in month t is irrational (overreaction) as the previous price pattern has reversed. Table 4 presents the results. For brevity, only equal-weighted EMC size-adjusted returns are reported in the main text. The Internet Appendix (Table IA.7) reports value-weighted returns.

As shown in Columns 1, 3, and 5, the coefficients of Ab_Temp are statistically insignificant. The coefficients of temperature quintiles in Columns 2, 4, and 6 do not show a systematic pattern and are generally statistically insignificant. These results indicate that there is no strong continuation or reversal in the 3 to 12 months after month t. (It is certainly possible that there is a return reversal after 12 months. With 17 years of data, longer term reversals are statistically difficult to detect. We encourage future research to test whether the belief updating process is rational or irrational with longer sample periods.)

A concern about the IPCC industry classification is that we may pick up some industry effects. Although it is not obvious why such effects would vary with local abnormal temperatures, we conduct three additional tests to further confirm our previous results. First, we rerun the return regressions in Equation (3) using an earlier sample period, 1983 (the beginning year of our abnormal temperature measures) to 2000. Unlike panel B of Table 3 (in which the sample period is 2001–2017), Columns 1 and 2 of Table 5 do not show any systematic difference in $EMISSION$ and $CLEAN$ portfolio returns under different abnormal temperatures. Climate change was less of a global concern and the scientific evidence was less conclusive before the 21st century. It is not surprising that we observe the return pattern globally only after 2001 if this is due to the awareness of climate risk.

Second, some high-emission industries' returns may be correlated with fluctuations in oil prices. Columns 3 to 6 separately examine all energy firms (which are in the IPCC Energy sector) and other high-emission firms (which are in the remaining four IPCC sectors). Both groups underperform when the city is abnormally warm. The results observed among nonenergy industries confirm that investors are more likely to react to different carbon emission levels than to oil prices.

Our third test defines high- and low-emission firms by their MSCI carbon emission scores. Because these scores are industry-adjusted, it is now possible to have both high- and low-emission firms in the same industry, and this test will not be driven by industry effects. Note that this analysis is performed with a smaller sample (with 14 exchanges), as MSCI scores are only available since 2007 and cover only a subset of exchanges and firms. The results in Columns 7 and 8 are in line with those of our previous tables. EMC earns lower returns when the city's Ab_Temp is high, especially when it is in the highest quintile. In Column 7, a 1-standard-deviation increase in Ab_Temp corresponds to a decrease of 38 bps in EMC size-adjusted return (t-stat $= -2.6$).

Columns 9 and 10 of Table 5 conduct another robustness check. Some exchange cities are small in total market capitalization and contain fewer firms. The tests in Section 3.5

require equity ownership data from FactSet, which generally covers larger stock exchanges. The *EMC* return results using this subset are similar to those in the full sample. Finally, Columns 11 and 12 include dummy variables that indicate the country of the exchange city is the ten largest in size in our sample. In our return regressions (Equation (3)), we use the exchange city's temperature to proxy for people's experience in the country. In larger countries where the population is more dispersed, this proxy will be weaker. We find that the relationship between the city's abnormal temperature and emission-minus-clean portfolio returns is indeed weaker in large countries.[14]

We explore other variables in our weather data in the Internet Appendix (Tables IA.9 and IA.10): average wind speed, maximum wind speed, precipitation, and snow depth. Abnormal weather conditions are defined in the same way as in Equation (1). There is no evidence that Google *DSVI* and *EMC* returns vary with these local conditions in a systematic manner. While some contemporaneous research establishes a link between institutional investors' increased perception of climate risk and extreme weather events in the United States (Gibson and Krueger 2018; Alok, Kumar, and Wermers forthcoming), we acknowledge that our current variables do not perfectly capture the occurrences of hurricanes (or typhoons), floods, and droughts. We invite future research to test these links again using better data on international extreme weather.

3.3 Belief updating process

Overall, our findings suggest that the *EMC* return is negative in abnormally warm weather. One might wonder why, after many years, we still see a reaction in a warm month—why is this update so slow? We offer two potential explanations. First, there is perhaps some reversal in beliefs. While we do not see a statistically significant return reversal in the 12 months after the abnormally warm month, this does not mean that there is no reversal in

[14] Table IA.8 in the Internet Appendix runs the return regressions by dropping all firms listed in the United States (on the New York Stock Exchange), which constitute a large part of our sample and have geographically diverse investor base. Our main results are robust to dropping firms listed in the United States.

beliefs at all (it may simply not be strong enough to be detected in the return data). Figure 1 offers more suggestive evidence: when we sort *EMC* portfolio returns into five abnormal temperature quintiles, Quintile 1 (the coolest quintile) shows a positive return, although it is not significant at the 5% level. We think some people revise their beliefs downward in an abnormally cool month, for example, President Donald Trump, as noted in the Introduction.

Additionally, it is possible that the learning process occurs at different times in different countries, and hence we see a generally slow update when we study exchange cities all over the world. The impact of climate change could have been felt in a small subset of countries even before it became a global issue. Following Hong, Li, and Xu (2019), we focus on countries that experienced increasing drought trends (that were possibly exacerbated by rising temperatures) in the second half of the 20th century. For example, in that period, Peru experienced disrupted water supplies, especially in dry seasons, as the tropical glaciers of the Cordillera Blanca shrank rapidly (Baraer et al. 2012). We identify these countries by estimating the time trend of the Palmer Drought Severity Index (PDSI) provided by Dai, Trenberth, and Qian (2004). The index measures drought intensity based on a model developed by Palmer (1965). Regression Equation (3) is run again with an interaction term of Ab_Temp and *Drought*, using *Early* (1983–2000) and *Late* sample periods (2001–2017). *Drought* is a dummy variable indicating countries that have a PDSI time trend in the lowest quintile and that experience worsening droughts. (These countries are Austria, Brazil, Israel, Italy, Japan, Peru, Saudi Arabia, Taiwan, and Venezuela.)

Table 6 shows the results. Column 1 shows that *EMC* returns react to Ab_Temp more negatively among *Drought* countries in the period 1983–2000. Column 3 presents similar findings in the highest Ab_Temp quintile. In 2001–2017, the point estimates in Columns 2 and 4 suggest that these countries show a slightly weaker response in *EMC* returns to high Ab_Temp. While our full-sample results in Table 3 show that people typically update their beliefs under warmer-than-usual temperatures in the period 2001–2017, countries that have reacted earlier may now show weaker reactions—as most people in these countries might have already become aware of climate change.[15]

3.4 Mechanism of the pricing effect

The above sections suggest that some investors are reacting to local weather conditions. Google search activity mostly originates from households, so we expect that retail investors (the majority of whom are local) have limited attention and react to abnormally warm local temperatures rather than to fundamental information. Upon recognizing the effect of climate change, they can update their beliefs about firms' valuation or stay away from climate-unfriendly stocks, as discussed in Section 1.

We confirm our conjecture in this section and the next section. First, we show that the return patterns are not entirely attributed to fundamental information about firms' valuation. Using high-emission firms in exchange cities with at least one foreign firm (forty-three cities), Columns 1 and 2 in Table 7, panel A, run a stock-level regression on local abnormal temperatures and check whether foreign firms listed on the local exchange show the same results.[16] Firms whose major operations are located in a foreign country will not see their production harmed by local weather conditions, but their returns are still influenced by local sentiment (see, e.g., Chan, Hameed, and Lau 2003). Although the stock-level results are weaker than EMC portfolio results in Table 3, we see high-emission firms' stock returns significantly decrease with Ab_Temp. More important, there is no significant difference between local and foreign firms in their price reaction to abnormal temperatures. Columns 3 and 4 repeat the tests using ten exchange cities with the highest proportion of foreign firms

[15] A median of 74% of people across countries in Latin America agree that climate change is a very serious problem in a 2015 survey conducted by The Pew Research Center (Stokes, Wike, and Carle 2015), compared with a global median is 54% (and 45% of Americans). Stokes, Wike, and Carle (2015) also note that fears of drought are particularly prevalent in Latin America. One can link our main findings to the reaction to stale or redundant information (Tetlock 2011; Huberman and Regev 2001). The scientific evidence of climate change is abundant, whereas abnormal local temperatures carry little new information. In *Drought* countries, the reaction to redundant information is weaker as people generally know more about the impact of climate change.

[16] We do not construct EMC portfolios here, because most countries have too few foreign firms. We also run stock-level regressions with the full sample in Table IA.11 in the Internet Appendix. The results are broadly consistent with those of the portfolio regressions.

(10% of all listed firms across these exchanges are foreign firms, and therefore the test of the difference between local and foreign firms has higher statistical power). Again, there is no significant difference, suggesting that the returns are driven by local investors.

Addoum, Ng, and Ortiz-Bobea (forthcoming) find that high temperature shocks can negatively affect companies' earnings in some industries. In particular, the following industries' earnings are harmed by extremely warm temperatures: Electric Utilities, Leisure Products, Construction and Engineering, Capital Markets, Gas Utilities, and Machinery. Four (Electric Utilities, Construction and Engineering, Gas Utilities, and Machinery) of these six industries are classified as high-emission industries according to our IPCC classifications.

In Columns 1 and 2 of Table 7, panel B, we form the $EMISSION$ portfolio using only firms in the above four industries (the $CLEAN$ portfolio remains the same).[17] Columns 3 and 4 form the $EMISSION$ portfolio using firms in all the remaining high-emission industries according to our IPCC classifications. While the first set of high-emission firms may suffer from negative earnings shocks, the second set is unlikely to be significantly affected by high temperatures. We obtain statistically significant results in both tests. Taken together, panels A and B of Table 7 suggest that our overall findings are not purely driven by adverse earnings news.[18]

However, investors may still update their private beliefs about firms' valuation as they become more aware of climate risk, even if in the absence of any real change in firms' valuation. While such beliefs are not observable, we examine cases in which future cashflows of high-emission firms are more harmed by climate change. If investors revise their estimates about future cashflows, the revisions would be more prominent under these situations, and

[17] They correspond to the following ICB industry codes in our paper: 7535 (Conventional Electricity), 2353 (Building Materials & Fixtures), 2357 (Heavy Construction), 3728 (Home Construction), 7573 (Gas Distribution), and 2757 (Industrial Machinery).

[18] The reaction is net of firms' hedging activities. Addoum, Ng, and Ortiz-Bobea (forthcoming) design a test using city-specific weather derivative introduction and discontinuation dates from the CME Group. They find that hedging activities using weather derivatives in the United States have a small impact on earnings sensitivities to temperatures. We believe that hedging activities of international firms have an even smaller impact, given the absence of weather derivatives in most countries. (It is possible to hedge climate change risk using other securities. For example, Engle et al. (forthcoming) propose to use a large panel of equity returns to build climate change hedge portfolios.)

we would observe a stronger negative link between high-emission firms' returns and local abnormal temperatures.

Table 7, panel C, analyze two examples of these situations. Columns 1 and 2 study periods when the carbon futures price is above the sample median. When the price of carbon is high, the production costs of carbon-intensive firms increase. Columns 3 and 4 use the environmental regulatory regime index developed by Esty and Porter (2001). We define a dummy variable, Reg_High, to denote countries in which the index is positive (the index is positive in 35 exchange cities from 27 countries; the quality of the environmental regulatory system is good in these countries). Tighter regulations in these places make it more costly to emit carbon. We do not observe stronger reactions in EMC returns to Ab_Temp when the carbon price is high and when the quality of regulations is good.[19] Therefore, there is no evidence that investors update their beliefs about firms' future cashflows in unusually warm months.

3.5 Trading behavior

Next, we turn to additional data to help us study the trading activity of different types of investors. As described in Section 2, we obtain data on blockholders' ownership and institutional ownership from DataStream and FactSet, respectively. Retail investors' ownership is defined as (100% − Blockholders' ownership − Institutional ownership excluding blockholders). Note that we do not observe retail ownership directly and the estimate is subject to measurement errors.

Trading activity is the change in ownership between two quarters. For example, if the retail ownership in a particular stock increases from 75% to 77% (of total shares outstanding), we infer that retail investors buy 2% in this quarter. Similar to returns, we calculate the

[19] The index is calculated based on information available in 2001. Investors may react to expected changes in future regulations instead. Table IA.12 in the Internet Appendix studies some of the most important international events, namely, the establishment of the Copenhagen Agreement in December 2009 and the Paris Agreement in November 2015 and the release of the IPCC Reports in February 2007 and September 2013, which might trigger tighter future regulations because of coordinated efforts and advances in scientific research. We do not observe a stronger link between EMC and Ab_Temp after these events.

EMC_Δ for each type of investors, defined as the average change in ownership in high-emission firms minus that in low-emission firms. Panel A of Table 8 reports the summary statistics.

We run regressions similar to Equation (3):

$$EMC\_\Delta_{it} = \alpha + \beta_1 Ab\_Temp_{it} + \Sigma_t YearQuarter_t + \epsilon_{it}, \tag{5}$$

where EMC_Δ_{it} is the average net buy across all high-emission firms (in exchange city i) minus the average net buy across all low-emission firms in quarter t, Ab_Temp_{it} is the abnormal temperature in city i in quarter t (defined in the same way as monthly Ab_Temp), and $YearQuarter_t$ are year-quarter fixed effects. A separate regression is run for each type of investors. We also run regressions by replacing Ab_Temp with abnormal temperature quintile dummies.

Panel B of Table 8 reports the results for retail investors (Columns 1 and 2), institutional investors excluding blockholders (Columns 3 and 4), and blockholders (Columns 5 and 6). In line with our expectation, retail investors reduce their holdings in high-emission firms under abnormally warm weather; in Column 1, the coefficient of Ab_Temp is negative and statistically significant (t-stat = 2.0). Column 2 shows that retail investors reduce their EMC holdings by 0.40% in the warmest temperature quintile compared to the coldest quintile. We do not find evidence that institutional investors alter their EMC holdings systematically according to local abnormal temperatures.[20]

Blockholders seem to respond to the decrease in stock prices and buy high-emission firms as Ab_Temp increases. This finding is similar to the idea that firms are buyers of last resort for their own stocks, and they repurchase shares when prices drop below their fundamental value (Hong, Wang, and Yu 2008).[21] Panel C of Table 8 shows the regressions for domestic

[20] Possibly, some institutions are net buyers and some are net sellers, and they appear constant when we sum them. In a survey to institutional investors around the world (Krueger, Sautner, and Starks forthcoming), most respondents believe that climate risks have financial implications for their portfolios. Examining whether this subset of investors reacts to local weather conditions will be interesting.

[21] Blockholders' trading patterns can be potentially explained two ways. First, high-emission firms are

institutions (Columns 1 and 2), foreign institutions (Columns 3 and 4), domestic blockholders (Columns 5 and 6), and foreign blockholders (Columns 7 and 8). Only domestic blockholders significantly increase their EMC ownership when the abnormal temperature increases.

Table 9 repeats the tests using MSCI scores (instead of IPCC industries) to define emission levels (panel A) and separately studies energy and nonenergy high-emission sectors (panel B). Similarly, retail investors reduce their holdings of high-emission firms in unusually warm quarters.[22] Because retail investors should not be more informed than domestic blockholders, we do not think retail investors are reacting to fundamental changes (confirming our argument in Section 3.4: the return results are not entirely driven by negative cashflow shocks). We interpret this as evidence that retail investors' changes in beliefs about climate risk move stock prices—they avoid holding high-emission firms as they become more aware of global warming. Institutional investors and blockholders, on the other hand, do not appear to update their beliefs in abnormally warm weather.

4 Conclusion

Surveys of the scientific literature show a 97%–98% consensus among scientists that humans are causing global warming (Cook et al. 2016, 2013; Anderegg et al. 2010; Oreskes 2004). Anthropogenic influence is evident from the emission of greenhouse gases such as

shunned by some retail investors; like sin stocks, they should earn high expected returns (Hong and Kaperczyk 2009). Table 3, panel A, shows that $EMISSION$ firms earn higher size-adjusted returns than $CLEAN$ firms unconditionally (2.2 bps per month vs. -2.2 bps (equal-weighted) and 3.2 bps vs. -6.8 bps (value-weighted)). Second, attention-induced price pressure reverses in the long run (although we cannot identify significant reversals in our tests). To examine the second explanation, Table IA.13 in the Internet Appendix checks whether the price reaction to abnormal temperatures is stronger under high investor attention. The evidence is mixed.

[22] While retail investors may not fully understand the nuance of industry-adjusted MSCI scores, we believe that they can identify some clean and emission firms, at least within some industries. For example, Toyota Motor Corporation (Virgin America) is a $CLEAN$ ($EMISSION$) firm according to MSCI scores. Toyota is widely recognized for its efforts to reduce vehicle CO_2 emissions, and it ranked top in Carbon Clean 200, a list of world's top clean companies. On the other hand, Virgin America has been criticized for its fuel efficiency by the media. A study by the International Council for Clean Transport shows that Virgin America produces more greenhouse gas emissions per passenger than other domestic U.S. carriers. Perhaps unsurprisingly, Japanese and U.S. retail investors can recognize these firms relative to their industry peers, given the media reports. Nevertheless, we urge the reader to interpret the results with caution.

CO_2 from human activities. Despite all these scientific facts, not everyone treats climate risk seriously and reacts to it—a U.S. survey (Marlon et al. 2016) estimates that only 70% of adults believe that global warming is happening, and 40% think it will harm them personally.[23] Global warming is an important long-term issue that requires collective action from humans, not just from climate scientists, to address. Our paper aims to understand how people update their beliefs about climate change.

One reason for the discrepancy between scientific findings and aggregate beliefs is that people have limited attention. The effects of climate risk are usually overlooked in normal times because they focus on attention-grabbing weather events and personal experiences. Consistent with this idea, we show that people revise their beliefs upward when the local temperature is abnormally warm. Google search activity on the topic "global warming" is greater. In financial markets, carbon-intensive firms underperform in the month in which the exchange city is warmer than usual. We find that retail investors, rather than institutional investors and blockholders, shun climate-unfriendly stocks and seem to be responsible for these price patterns. While climate change is a long-term trend, local temperatures are more noticeable even though they contain negligible information about the global trend. Retail investors react to salient but uninformative weather events, and their beliefs and actions are reflected in prices and trading activity.

We document evidence that people in countries where the impact of climate was more prominent in the past suffer less from limited attention. To increase public awareness and the efficacy of climate campaigns, policies that reduce the information gaps between the scientific community and the general public will be helpful. For example, people are more concerned about flood risk after the disclosure of high-resolution flood maps in Finland, resulting in

[23] Opinions vary across different parts of the United States, which are reflected in housing prices in the neighborhood (Baldauf, Garlappi, and Yannelis forthcoming). Global surveys also suggest that climate change deniers are present all over the world and that the proportion of deniers varies by country. Only 42% of surveyed adults worldwide (53% in the United States, 57% in the United Kingdom, and 50% in France) see global warming as a serious threat (results come from Gallup surveys in 111 countries in 2010). The Gallup report is available at `https://news.gallup.com/poll/147203/Fewer-Americans-Europeans-View-Global-Warming-Threat.aspx`.

a price drop in coastal properties (Votsis and Perrels 2016). Although governments and environmental organizations are not able to alter local weather conditions, they can educate the public on climate risk. The findings in our paper suggest that methods relating to personal and salient experiences (e.g., simulated extreme weather events, maps of potential sea-level rise) will be more effective. When aggregate beliefs are closer to the scientific consensus, we expect to see weaker links between local abnormal temperatures and attention and stock prices, but a more organized global effort to fight climate change.

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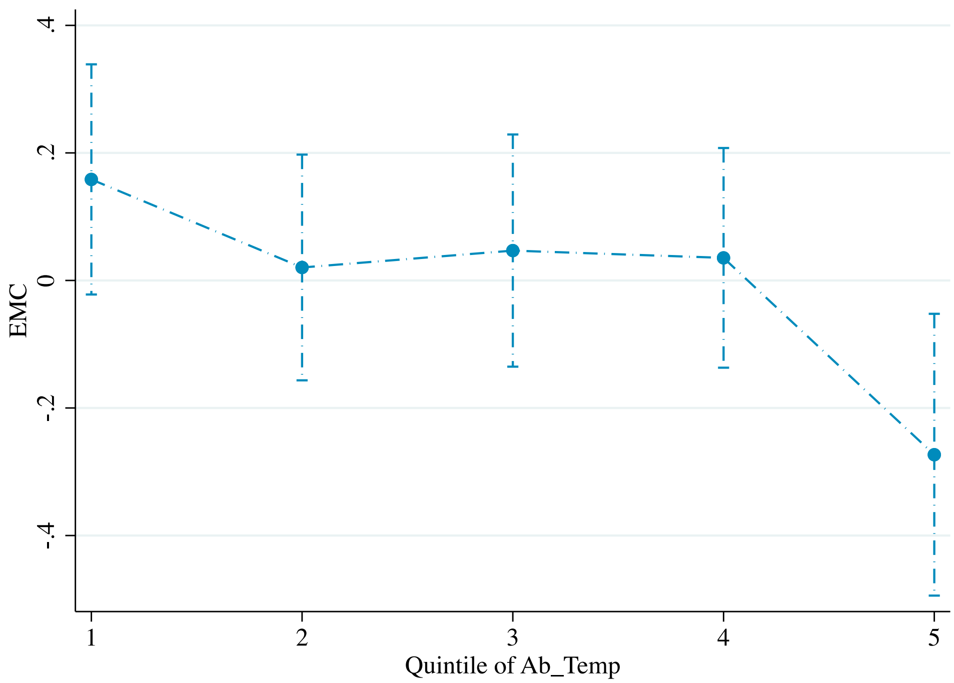
Figure 1. EMC on abnormal temperature, 2001–2017



The figure presents the average EMC returns (equal-weighted and adjusted for year-month fixed effects, as a %) by Ab_Temp quintiles with 95% confidence intervals using the sample for 2001–2017.

Table 1. List of exchange cities

This table lists the seventy-four exchange cities (and their countries/areas and continents) that we use in analyses and the number of unique firms, number of foreign firms (whose home country information is available and is different from that of the exchange city), number of emission firms and foreign emission firms (defined by the IPCC classification), and average retail and blockholder ownerships in each city during the sample period, from 2001 to 2017.

City	Country /area	Continent	#Firms	#Foreign	#Emission	#Foreign emission	%Retail	%Blockholder
Amman	Jordan	Asia	228	0	56	0		
Amsterdam	Netherlands	Europe	247	10	68	2	51.47	2.67
Athens	Greece	Europe	364	0	141	0	59.12	0.69
Bangkok	Thailand	Asia	796	0	315	0		
Berlin	Germany	Europe	54	4	11	3	72.86	2.16
Bern	Switzerland	Europe	18	1	2	1		
Bogota	Colombia	South America	74	1	27	1		
Bratislava	Slovakia	Europe	25	0	8	0		
Brussels	Belgium	Europe	280	3	63	0	41.55	0.53
Bucharest	Romania	Europe	272	0	146	0		
Budapest	Hungary	Europe	77	1	23	0		
Buenos Aires	Argentina	South America	97	0	58	0		
Busan	Korea	Asia	1,006	2	466	1		
Cairo	Egypt	Africa	198	0	79	0		
Colombo	Sri Lanka	Asia	294	0	81	0		
Copenhagen	Denmark	Europe	285	4	71	3	48.30	3.27
Dhaka	Bangladesh	Asia	410	0	123	0		
Dublin	Ireland	Europe	76	4	24	3	54.03	8.30
Dusseldorf	Germany	Europe	58	1	17	1	76.86	0.01
Frankfurt	Germany	Europe	1,735	69	462	17	43.06	0.94
Hamburg	Germany	Europe	65	1	9	0	49.19	1.73
Hanoi	Vietnam	Asia	400	0	258	0		
Harare	Zimbabwe	Africa	71	0	27	0		
Helsinki	Finland	Europe	208	1	70	1	51.70	2.89
Ho Chi Minh	Vietnam	Asia	340	0	181	0		
Hong Kong	Hong Kong	Asia	2,064	646	650	251	38.95	0.38
Istanbul	Turkey	Europe	461	0	167	0		
Jakarta	Indonesia	Asia	592	0	233	0		
Johannesburg	South Africa	Africa	663	14	196	4	55.97	1.57
Karachi	Pakistan	Asia	410	0	153	0		
Kiev	Ukraine	Europe	83	0	61	0		
Kuala Lumpur	Malaysia	Asia	1,207	12	574	3		
Kuwait	Kuwait	Asia	177	0	39	0		
Lagos	Nigeria	Africa	160	1	55	0		
Lima	Peru	South America	140	3	85	3		
Lisbon	Portugal	Europe	97	1	38	0	36.73	0.73
Ljubljana	Slovenia	Europe	137	0	51	0		

London	United Kingdom	Europe	3,558	440	940	165	58.34	2.15
Luxembourg	Luxembourg	Europe	38	3	8	0	58.09	0.45
Madrid	Spain	Europe	298	2	97	1	45.97	0.33
Manila	Philippines	Asia	283	0	99	0		
Mexico City	Mexico	North America	183	0	67	0		
Milan	Italy	Europe	519	8	152	4	46.68	0.55
Moscow	Russia	Europe	349	0	259	0		
Mumbai	India	Asia	4,806	1	1,908	0	46.02	1.12
Munich	Germany	Europe	90	2	18	0	55.26	3.54
Muscat	Oman	Asia	98	0	41	0		
Nagoya	Japan	Asia	116	0	47	0	66.50	0.69
New York City	United States	North America	3,874	324	1,026	121	30.26	11.08
Nicosia	Cyprus	Europe	143	4	36	0		
Osaka	Japan	Asia	140	0	46	0	62.59	0.04
Oslo	Norway	Europe	446	52	234	45	39.39	2.74
Paris	France	Europe	1,578	37	382	6	40.98	0.85
Prague	Czechia	Europe	71	3	40	0		
Riyadh	Saudi Arabia	Asia	182	0	72	0		
Santiago	Chile	South America	236	0	100	0		
Sao Paulo	Brazil	South America	297	2	136	2		
Shanghai	China	Asia	1,180	0	613	0		
Shenzhen	China	Asia	2,024	0	1,093	0		
Singapore	Singapore	Asia	920	140	443	70	40.36	0.62
Skopje	Macedonia	Europe	40	0	20	0		
Sofia	Bulgaria	Europe	157	0	41	0		
Stockholm	Sweden	Europe	1,102	27	292	7	59.45	2.86
Stuttgart	Germany	Europe	55	5	12	3	40.86	0.64
Sydney	Australia	Oceania	2,888	93	1,502	37	72.78	0.59
Taipei	Taiwan	Asia	1,023	34	556	19		
Tel Aviv	Israel	Asia	785	7	251	0		
Tokyo	Japan	Asia	3,656	2	1,465	0	70.39	0.52
Toronto	Canada	North America	841	39	395	27	49.02	6.54
Vienna	Austria	Europe	166	2	65	0	31.80	0.47
Warsaw	Poland	Europe	1,075	23	339	8	29.39	3.49
Wellington	New Zealand	Oceania	229	5	62	1		
Zagreb	Croatia	Europe	73	0	27	0		
Zurich	Switzerland	Europe	367	15	119	2	63.68	0.68

Table 2. Google search volume for "global warming" and abnormal temperature

This table reports the results of analyses on the effect of abnormal temperatures on the search volume of the topic of "global warming" on Google. Panel A presents summary statistics of the variables. *DSVI(city)* is the monthly log change of Google's search volume index (SVI) of the topic "global warming" in the exchange city and adjusted for seasonality, and *DSVI(country)* is calculated using the SVI in country of the city. *Aver_ Temp* is the average monthly temperature (in Fahrenheit degrees) of the exchange's city over the previous 120 months. *Mon_ Temp* is the city's average temperature in the same month of the year over the previous 10 years minus *Aver_ Temp*. *Ab_ Temp* is the city's temperature in this month minus *Aver_ Temp* and *Mon_ Temp*. Panel B represents the result of regressing *DSVI(city)* (Columns 1 and 2) and *DSVI(country)* (Columns 3 and 4) on city-level temperature measures. For each exchange city, months are sorted into quintiles based on *Ab_ Temp*, and *Ab_ Temp Q2-Q5* are quintile dummies that equal one if the month belongs to quintiles 2–5, respectively. The sample is from 2004 to 2017. Standard errors are clustered by exchange city and by year-month, and the corresponding t-statistics are reported in parentheses. *$p <.1$; **$p <.05$; ***$p <.01$.

A. Summary statistics

Variable	Obs	Mean	SD	P10	P25	P50	P75	P90
DSVI(city)	11,603	-0.017	66.484	-51.333	-23.129	-0.604	22.652	51.584
DSVI(country)	10,366	0.047	77.578	-57.793	-24.908	-1.506	22.644	59.254
Aver_Temp	11,603	61.861	12.454	48.334	51.655	59.458	72.406	81.695
Mon_Temp	11,603	0.155	10.837	-15.185	-8.069	0.259	8.178	15.506
Ab_Temp	11,603	0.265	2.679	-2.794	-1.201	0.238	1.696	3.419
#Exchange cities	72							

B. Regression of DSVI on abnormal temperature

	(1) DSVI(city)	(2) DSVI(city)	(3) DSVI(country)	(4) DSVI(country)
Ab_Temp	0.536**		0.724**	
	(2.26)		(2.43)	
Ab_Temp Q2		0.630		-0.279
		(0.34)		(-0.16)
Ab_Temp Q3		1.220		-1.787
		(0.84)		(-1.00)
Ab_Temp Q4		1.074		-1.149
		(0.58)		(-0.47)
Ab_Temp Q5		4.841**		3.539
		(2.57)		(1.66)
Year $\times$ Month FEs	Yes	Yes	Yes	Yes
Obs.	11,603	11,603	10,366	10,366
Adj. R^2	.020	.020	.015	.015

Table 3. Emission-minus-clean portfolio return and abnormal temperature

At the beginning of month t, $EMISSION$ and $CLEAN$ portfolios are formed based on firms' industry code. High-carbon-emission industries are defined following the IPCC's report. Portfolio return (as a percentage) equals the average adjusted return of stocks at month t, equal weighted or value weighted. Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. EMC equals $EMISSION$ minus $CLEAN$. $EMC(raw)$ is calculated using raw returns. $EMC_{t+1,t+3}$, $EMC_{t+1,t+6}$, and $EMC_{t+1,t+12}$ are calculated using adjusted returns over months $t+1$ to $t+3$, $t+1$ to $t+6$ and $t+1$ to $t+12$, respectively. Panel A reports summary statistics. Panel B reports the results of regressions of EMC on contemporaneous temperature variables using equal-weighted portfolio returns, and panel C uses value-weighted returns. The sample is from January 2001 to December 2017. Standard errors are clustered by exchange city and year-month, and the corresponding t-statistics are reported in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

A. Summary statistics

Variable	Obs	Mean	SD	P10	P25	P50	P75	P90
Equal-weighted								
EMC	12,614	0.044	4.867	-3.528	-1.464	0.000	1.657	3.819
EMC(raw)	12,614	0.060	5.728	-4.189	-1.692	0.112	1.926	4.519
EMISSION	12,614	0.022	3.269	-2.060	-0.829	0.000	0.957	2.251
CLEAN	12,614	-0.022	2.002	-1.391	-0.605	0.000	0.535	1.368
$EMC_{t+1,t+3}$	12,614	0.057	6.614	-5.605	-2.269	0.142	2.663	5.821
$EMC_{t+1,t+6}$	12,614	0.122	9.089	-8.379	-3.326	0.272	4.157	8.532
$EMC_{t+1,t+12}$	12,614	0.276	12.908	-12.533	-4.969	0.672	6.601	13.078
Value-weighted								
EMC	12,614	0.100	5.999	-5.155	-2.210	0.047	2.507	5.609
EMC(raw)	12,614	0.117	6.710	-5.628	-2.415	0.121	2.713	6.096
EMISSION	12,614	0.032	4.263	-3.545	-1.536	0.001	1.693	3.776
CLEAN	12,614	-0.068	3.108	-2.936	-1.348	-0.019	1.192	2.813
Ab_Temp	12,614	0.307	2.676	-2.776	-1.142	0.306	1.746	3.446

B. Equal-weighted EMC returns

	(1)	(2)	(3)	(4)	(5)	(6)
	EMC		EMC(raw)		EMISSION	CLEAN
Ab_Temp	-0.060***		-0.068***			
	(-3.34)		(-2.67)			
Ab_Temp Q2		-0.148		-0.297*	-0.035	0.113*
		(-1.16)		(-1.69)	(-0.44)	(1.90)
Ab_Temp Q3		-0.125		-0.316	-0.041	0.084
		(-0.88)		(-1.60)	(-0.41)	(1.47)
Ab_Temp Q4		-0.145		-0.212	-0.094	0.051
		(-1.27)		(-1.63)	(-1.52)	(0.90)
Ab_Temp Q5		-0.481***		-0.614***	-0.285***	0.196***
		(-4.04)		(-3.82)	(-3.35)	(3.95)
Year × Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,614	12,614	12,614	12,614	12,614	12,614
Adj. R^2	.020	.020	.018	.018	.014	.022

C. Value-weighted EMC returns

	(1)	(2)	(3)	(4)	(5)	(6)
	EMC		EMC(raw)		EMISSION	CLEAN
Ab_Temp	-0.055**		-0.066**			
	(-2.08)		(-2.00)			
Ab_Temp Q2		-0.211		-0.317	-0.069	0.142
		(-1.13)		(-1.37)	(-0.63)	(1.34)
Ab_Temp Q3		-0.337*		-0.522**	-0.202*	0.135
		(-1.79)		(-2.23)	(-1.77)	(1.33)
Ab_Temp Q4		-0.310*		-0.441**	-0.174	0.136
		(-1.78)		(-2.42)	(-1.64)	(1.52)
Ab_Temp Q5		-0.476***		-0.574***	-0.324***	0.152
		(-3.06)		(-2.81)	(-3.10)	(1.60)
Year × Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,614	12,614	12,614	12,614	12,614	12,614
Adj. R^2	.036	.036	.033	.033	.028	.032

Table 4. Long-term EMC returns subsequent to abnormal temperature

The table reports the results of regressions of $EMC_{t+1,t+3}$, $EMC_{t+1,t+6}$, and $EMC_{t+1,t+12}$ on abnormal temperature variables at month t. All EMC returns are calculated using the equal-weighted average of adjusted returns. The sample is from January 2001 to December 2017. Standard errors are clustered by exchange city and year-month, and the corresponding t-statistics are reported in parentheses. *$p <.1$; **$p <.05$; ***$p <.01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\text{EMC}_{t+1,t+3}$		$\text{EMC}_{t+1,t+6}$		$\text{EMC}_{t+1,t+12}$	
Ab_Temp	-0.048		-0.012		-0.001	
	(-1.40)		(-0.38)		(-0.01)	
Ab_Temp Q2		-0.303		-0.070		-0.005
		(-1.41)		(-0.26)		(-0.01)
Ab_Temp Q3		-0.189		-0.050		-0.126
		(-1.44)		(-0.21)		(-0.31)
Ab_Temp Q4		-0.431**		-0.127		-0.138
		(-2.64)		(-0.50)		(-0.33)
Ab_Temp Q5		-0.358		-0.061		0.348
		(-1.56)		(-0.26)		(0.82)
Year × Month FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	12,614	12,614	12,614	12,614	12,614	12,614
Adj. R^2	.034	.034	.048	.047	.053	.053

Table 5. EMC return and abnormal temperature: Robustness tests

This table presents results of several robustness tests of the analysis in Table 3. Columns 1 and 2 are placebo tests: regressions of EMC on contemporaneous temperature variables from January 1983 to December 2000. $EMISSION$ and $CLEAN$ portfolios are formed based on firms' industry codes. High-carbon-emission industries are defined following the IPCC's report. Portfolio return (as a percentage) is the equal weighted average adjusted return of stocks at month t. Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. EMC equals $EMISSION$ minus $CLEAN$. In Columns 3 to 6, the $EMISSION$ portfolio is divided by Energy and Nonenergy firms, and EMC portfolio returns are calculated for each group. In Columns 7 and 8, $EMISSION$ and $CLEAN$ firms are categorized using MSCI ratings: $EMISSION$ includes stocks with carbon emission scores lower than 3, whereas the $CLEAN$ portfolio consists of stocks with carbon emission scores higher than 7. This sample is from January 2008 to December 2017 and includes only exchanges with more than thirty stocks covered by MSCI. In Columns 9 and 10, the sample includes only exchanges in the FactSet database. Columns 11 and 12 include dummy variables that indicate the country of the exchange city is the ten largest in size in our sample (the countries are Russia, Canada, China (two exchanges), United States, Brazil, Australia, India, Argentina, and Saudi Arabia). In all columns, standard errors are clustered by exchange city and year-month, and the corresponding t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Placebo		Energy		Nonenergy		MSCI		FactSet		Top-10 areas	
Ab_Temp	0.000		-0.084**		-0.048**		-0.143**		-0.058**		-0.075***	
	(0.01)		(-2.58)		(-2.26)		(-2.60)		(-2.16)		(-3.66)	
Ab_Temp Q2		0.117		-0.126		-0.168		-0.415		-0.083		-0.149
		(0.54)		(-0.55)		(-1.25)		(-0.68)		(-0.79)		(-1.17)
Ab_Temp Q3		0.146		-0.282		-0.076		-0.853*		0.028		-0.126
		(0.60)		(-1.30)		(-0.51)		(-1.92)		(0.11)		(-0.88)
Ab_Temp Q4		0.115		-0.198		-0.116		-0.151		-0.136		-0.146
		(0.65)		(-1.07)		(-0.94)		(-0.36)		(-0.92)		(-1.28)
Ab_Temp Q5		-0.035		-0.402*		-0.491***		-0.935*		-0.569**		-0.507***
		(-0.18)		(-1.89)		(-3.60)		(-1.99)		(-2.50)		(-3.66)
Top10_Area											-0.033	-0.036
											(-0.26)	(-0.29)
Ab_Temp × Top10_Area											0.079**	
											(2.36)	
Ab_Temp Q5 × Top10_Area												0.156
												(0.63)
Year × Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	8,997	8,997	10,744	10,744	12,537	12,537	784	784	5,788	5,788	12,614	12,614
Adj. R^2	.015	.015	.041	.040	.015	.015	.258	.255	.034	.035	.020	.020

Table 6. EMC return and abnormal temperature: Additional tests

At the beginning of month t, EMISSION and CLEAN portfolios are formed based on firms' industry codes. High-carbon-emission industries are defined following the IPCC's report. Portfolio return (as a percentage) equals the equal-weighted average adjusted return of stocks. Adjusted return equals the raw return minus the average return of stocks in the same size quintile by each exchange. EMC equals EMISSION minus CLEAN. See Table 2 for definitions of *Ab_ Temp* and *Ab_ Temp Q2-Q5*. *Drought* equals one if the country is ranked in the bottom quintile based on long-term drought trends. Each country's long-term drought trend is estimated based on the Palmer Drought Severity Index (PDSI) from 1900 to 2014 following the method in Hong, Li, and Xu (2019). Columns 1 and 3 labeled as "Early" refers to a regression using the sample from January 1983 to December 2000, whereas "Late" refers to January 2001 to December 2017. In all regressions, standard errors are clustered by exchange city and year-month, and the corresponding t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

	(1) Early	(2) Late	(3) Early	(4) Late
Ab_Temp	0.035*	-0.054**		
	(1.81)	(-2.32)		
Drought	0.144	0.102	0.329	0.028
	(0.96)	(0.88)	(1.50)	(0.28)
Ab_Temp × Drought	-0.153*	0.015		
	(-1.84)	(0.43)		
Ab_Temp Q2			0.087	-0.100
			(0.35)	(-0.93)
Ab_Temp Q3			0.225	-0.087
			(0.83)	(-0.53)
Ab_Temp Q4			0.192	-0.161
			(1.04)	(-1.42)
Ab_Temp Q5			0.290	-0.549***
			(1.47)	(-3.29)
Ab_Temp Q5 × Drought			-1.237**	0.416
			(-2.02)	(1.49)
Year × Month FEs	Yes	Yes	Yes	Yes
Obs.	7,804	9,131	7,804	9,131
Adj. R^2	.019	.034	.019	.034

Table 7. EMC return and abnormal temperature: Additional tests

Panel A of this table reports results of regressions of individual stocks' adjusted returns on contemporaneous abnormal temperate. Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. *Foreign* equals one if it is a foreign firm listed on the local exchange, and zero if it is a local firm (firms with missing home country information are dropped). See Table 2 for definitions of *Ab_ Temp* and *Ab_ Temp Q2-Q5*. Columns 1 and 2 include exchanges with foreign firms, and Columns 3 and 4 use ten exchange cities with the highest proportion of foreign firms (Hong Kong, Singapore, London, Oslo, New York City, Toronto, Frankfurt, Taipei, Sydney, and Stockholm). In panel B, at the beginning of month t, EMISSION and CLEAN portfolios are formed based on firms' industry codes. In Columns 1 and 2, high-carbon-emission industries include Electric Utilities, Leisure Products, Construction and Engineering, Capital Markets, Gas Utilities, and Machinery. In Columns 3 and 4, high-carbon-emission industries include all the remaining high-emission industries according to the IPCC's report. Portfolio return (as a percentage) equals the equal-weighted average adjusted return of stocks. EMC equals EMISSION minus CLEAN. In Panel C, *High_ Price* is a dummy variable that equals one if the carbon price is in the upper half of all months. *Reg_ High* is a dummy variable that equals one if the regulation environment score in the country is positive (twenty-seven countries), and zero if it is negative (twenty-five countries); countries with missing scores are dropped. The sample is from January 2001 to December 2017. In all regressions, standard errors are clustered by exchange city and year–month, and the corresponding t-statistics are reported in parentheses. *p $<.1$; **$p<.05$; ***$p<.01$.

A. Local and foreign firms

	(1)	(2)	(3)	(4)
Dep. var.: Return	All exchanges with foreign firms		Top-10 exchanges	
Ab_Temp	-0.021*		-0.029*	
	(-1.79)		(-2.09)	
Foreign	-0.493*	-0.496*	-0.390	-0.407
	(-1.97)	(-1.95)	(-1.47)	(-1.46)
Ab_Temp × Foreign	-0.024		-0.008	
	(-0.91)		(-0.32)	
Ab_Temp Q2		-0.036		-0.139
		(-0.43)		(-1.00)
Ab_Temp Q3		-0.195**		-0.149
		(-2.46)		(-1.36)
Ab_Temp Q4		-0.021		-0.033
		(-0.28)		(-0.25)
Ab_Temp Q5		-0.135		-0.228
		(-1.29)		(-1.48)
Ab_Temp Q5 × Foreign		-0.008		0.070
		(-0.06)		(0.62)
Year × Month FEs	Yes	Yes	Yes	Yes
Obs.	808,211	808,211	515,466	515,466
Adj. R^2	.006	.006	.009	.009

B. High-emission firms that may be harmed by extremely warm temperatures

	(1)	(2)	(3)	(4)
Dep. var.: EMC	Harmed		Not harmed	
Ab_Temp	-0.086***		-0.048***	
	(-2.94)		(-2.76)	
Ab_Temp Q2		-0.356		-0.146
		(-1.47)		(-1.08)
Ab_Temp Q3		-0.309**		-0.113
		(-2.55)		(-0.73)
Ab_Temp Q4		-0.398*		-0.081
		(-1.92)		(-0.65)
Ab_Temp Q5		-0.590***		-0.441***
		(-3.10)		(-3.68)
Year × Month FEs	Yes	Yes	Yes	Yes
Obs.	11,789	11,789	12,513	12,513
Adj. R^2	.006	.006	.019	.019

C. Carbon prices and environmental regulation scores

	(1) EMC	(2) EMC	(3) EMC	(4) EMC
Ab_Temp	-0.038		-0.096*	
	(-1.32)		(-1.86)	
Ab_Temp × High_Price	-0.015			
	(-0.27)			
Reg_High			0.041	0.064
			(0.30)	(0.50)
Ab_Temp × Reg_High			0.045	
			(0.74)	
Ab_Temp Q2		-0.186		-0.045
		(-1.26)		(-0.32)
Ab_Temp Q3		-0.148		-0.090
		(-0.84)		(-0.55)
Ab_Temp Q4		-0.090		-0.171
		(-0.66)		(-1.45)
Ab_Temp Q5		-0.325**		-0.435**
		(-2.07)		(-2.29)
Ab_Temp Q5 × High_Price		-0.086		
		(-0.42)		
Ab_Temp Q5 × Reg_High				-0.075
				(-0.22)
Year × Month FEs	Yes	Yes	Yes	Yes
Obs.	9,541	9,541	10,590	10,590
Adj. R^2	.016	.016	.023	.022

Table 8. EMC of trading and abnormal temperature

At the beginning of quarter t, EMISSION and CLEAN portfolios are formed based on firms' industry codes. High-carbon-emission industries are defined following the IPCC's report. EMC_ΔRetail refers to the difference in the average changes in retail investors' ownership over the quarter between emission and clean firms (as a percentage). EMC_ΔInstitution and EMC_ΔBlockholder refer to changes in ownership by institutional investors and blockholders, respectively. Blockholders are those who own more than 5% of shares outstanding, whereas institutional investors include mutual funds, banks, and others but exclude those who are blockholders. Institutional investors and blockholders are further divided into domestic and foreign investor categories. Panel A reports the summary statistics of key variables, and panels B and C report the results of regressions of the EMC of ownership changes on abnormal temperature variables, which are defined in Table 2. In all regressions, year-quarter fixed effects are also included. The sample is from January 2001 to December 2016. Standard errors are clustered by exchange city and year-quarter, and the corresponding t-statistics are reported in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

A. Summary statistics

%	Obs	Mean	SD	P10	P25	P50	P75	P90
EMC_ΔRetail	2,008	-0.007	2.345	-0.942	-0.315	-0.015	0.298	0.924
EMC_ΔInstitution	2,008	0.006	0.317	-0.229	-0.070	0.000	0.076	0.245
EMC_ΔDomInstitution	2,008	-0.004	0.222	-0.114	-0.032	0.000	0.025	0.107
EMC_ΔForInstitution	2,008	0.009	0.199	-0.138	-0.038	0.000	0.052	0.161
EMC_ΔBlockholder	2,008	-0.003	2.344	-0.917	-0.271	0.000	0.279	0.884
EMC_ΔDomBlockholder	2,008	0.000	2.098	-0.761	-0.201	0.000	0.194	0.698
EMC_ΔForBlockholder	2,008	-0.012	1.320	-0.214	-0.025	0.000	0.034	0.174
#Exchange cities	33							

B. Stock trading on abnormal temperature

	(1)	(2)	(3)	(4)	(5)	(6)
	EMC_ΔRetail		EMC_ΔInstitution		EMC_ΔBlockholder	
Ab_Temp	-0.080*		0.003		0.077**	
	(-2.01)		(0.84)		(2.08)	
Ab_Temp Q2		-0.102		0.012		0.064
		(-0.67)		(0.89)		(0.40)
Ab_Temp Q3		-0.165		-0.001		0.132
		(-1.18)		(-0.05)		(0.96)
Ab_Temp Q4		-0.316**		0.005		0.303**
		(-2.22)		(0.31)		(2.32)
Ab_Temp Q5		-0.396		0.037*		0.362
		(-1.62)		(1.76)		(1.50)
Year × Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,008	2,008	2,008	2,008	2,008	2,008
Adj. R^2	.006	.003	.021	.021	.003	.001

C. Stock trading for domestic and foreign investors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	EMC_ΔDomInstitution		EMC_ΔForInstitution		EMC_ΔDomBlockholder		EMC_ΔForBlockholder	
Ab_Temp	0.002		0.001		0.047*		0.023	
	(0.99)		(0.46)		(1.94)		(0.94)	
Ab_Temp Q2		0.007		0.002		0.003		0.036
		(1.08)		(0.24)		(0.02)		(0.39)
Ab_Temp Q3		0.017		-0.017		0.147		-0.040
		(1.25)		(-1.19)		(1.69)		(-0.48)
Ab_Temp Q4		-0.010		0.018**		0.277*		-0.006
		(-1.11)		(2.07)		(1.83)		(-0.08)
Ab_Temp Q5		0.039		-0.001		0.128		0.172
		(1.66)		(-0.07)		(1.31)		(1.03)
Year × Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,008	2,008	2,008	2,008	2,008	2,008	2,008	2,008
Adj. R^2	.013	.016	.012	.013	-.006	-.007	.005	.005

Table 9. EMC of trading and abnormal temperature: Robustness test

In panel A, *EMISSION* and *CLEAN* firms are categorized using MSCI ratings: *EMISSION* includes stocks with carbon emission scores lower than 3, whereas the *CLEAN* portfolio consists of stocks with carbon emission scores higher than 7. EMC_ΔRetail refers to the difference in average changes of retail investors' ownership over the quarter between emission and clean firms (as a percentage). EMC_ΔInstitution and EMC_ΔBlockholder refer to changes in ownership by institutional investors and blockholders, respectively. Blockholders are those who own more than 5% of shares outstanding, whereas institutional investors include mutual funds, banks, and others but exclude those who are blockholders. In panel B, *EMISSION* and *CLEAN* firms are categorized based on firms' industry codes. High-carbon-emission industries are defined following the IPCC's report. The *EMISSION* portfolio is divided into energy and nonenergy firms, and the *EMC* portfolio is calculated for each group. In both panels, the EMC of ownership changes is regressed on abnormal temperature variables, which are defined in Table 2, with year-quarter fixed effects. The sample is from January 2001 to December 2016. Standard errors are clustered by exchange city and year–month, and the corresponding t-statistics are reported in parentheses. *$p<.1$; **$p<.05$; ***$p<.01$.

A. Using MSCI carbon emission scores

	(1)	(2)	(3)	(4)	(5)	(6)
	EMC_ΔRetail		EMC_ΔInstitution		EMC_ΔBlockholder	
Ab_Temp	-0.075		0.006		0.061	
	(-1.65)		(0.24)		(1.36)	
Ab_Temp Q2		-0.215		0.037		0.244
		(-0.79)		(0.33)		(1.09)
Ab_Temp Q3		0.028		-0.140		0.189
		(0.12)		(-1.03)		(0.91)
Ab_Temp Q4		-0.175		-0.054		0.156
		(-0.81)		(-0.48)		(0.79)
Ab_Temp Q5		-0.289***		-0.067		0.296
		(-3.21)		(-0.42)		(1.74)
Year × Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	312	312	312	312	312	312
Adj. R^2	.019	.006	-.003	-.007	.018	.005

B. Stock trading for energy/nonenergy firms

	Energy						Nonenergy					
	EMC_ΔRetail		EMC_ΔInstitution		EMC_ΔBlockholder		EMC_ΔRetail		EMC_ΔInstitution		EMC_ΔBlockholder	
Ab_Temp	-0.046*		0.019**		0.028		-0.082*		0.001		0.080*	
	(-1.77)		(2.55)		(1.02)		(-1.89)		(0.22)		(2.03)	
Ab_Temp Q2		-0.030		0.026		-0.016		-0.085		0.006		0.053
		(-0.16)		(0.48)		(-0.09)		(-0.57)		(0.45)		(0.33)
Ab_Temp Q3		-0.287**		0.008		0.265		-0.145		-0.010		0.113
		(-2.06)		(0.19)		(1.62)		(-1.05)		(-0.44)		(0.79)
Ab_Temp Q4		-0.127		0.058		0.052		-0.308**		-0.003		0.302**
		(-0.53)		(1.19)		(0.22)		(-2.29)		(-0.15)		(2.46)
Ab_Temp Q5		-0.393*		0.067		0.337		-0.366		0.029		0.338
		(-1.72)		(1.43)		(1.56)		(-1.51)		(1.23)		(1.43)
Year × Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,708	1,708	1,708	1,708	1,708	1,708	2,008	2,008	2,008	2,008	2,008	2,008
Adj. R^2	.016	.016	.006	.003	.019	.020	.003	.000	.018	.018	-.000	-.003