HEC Master Thesis :
Attention to Global Warming

Autors :

Gabriel HAYOUN

Edouard LELANDAIS

Supervisor :

Thierry FOUCAULT

Final version of

June 17, 2024

Abstract

This thesis explores how behavioral finance principles, such as overconfidence and familiarity biases, influence investor reactions to global warming. Specifically, it examines the impact of abnormally high temperatures on public attention to climate change and stock market performance. Using Google Trends data, we find that public interest in global warming spikes during extreme temperature anomalies. Financial analysis reveals that firms in polluting industries underperform relative to sustainable firms during unusually warm periods. However, the significance of this correlation diminishes in recent years, suggesting changing market dynamics. The study critiques the original methodology of Choi, Gao, and Jiang (2017) [1], highlighting issues with data selection and classification criteria, and underscores the importance of robust data preprocessing in big data analysis. Our findings contribute to understanding the nuanced ways in which climate events affect market behavior and investor sentiment.

Contents

1 Introduction: Motivation for the study

Behavioral finance suggests that investors often exhibit overconfidence regarding salient events, heavily weighting their personal experiences in a non-Bayesian manner. They tend to anchor their beliefs based on recent events they have encountered, leading to an overgeneralization of local observations. For instance, Gallagher (2014) [2] demonstrated a correlation between experiencing flood disasters and subsequent flood insurance subscriptions, suggesting that individuals irrationally overestimate the likelihood of future floods after experiencing one. Additionally, investors are susceptible to familiarity biases, such as the home bias, where they focus more on events and stocks that are geographically closer to them. This bias is influenced by the availability of news through local media, the presence of relatives working in local companies, as well as fiscal benefits on national stocks and patriotism.

Given this behavioral framework, it is plausible to anticipate a bias concerning global warming: people are more likely to feel concerned about global warming when they experience its effects personally. This study aims to examine the impact of abnormally high temperatures in major cities worldwide on the inhabitants' attention to global warming. Furthermore, we hypothesize that investors' overconfidence in response to salient events will influence stock prices, particularly those of companies depending on the sustainability of their industries.

In 2017, Darwin Choi, Zhenyu Gao, and Wenxi Jiang [1] found that "people revise their beliefs about climate change upward when experiencing warmer than usual temperatures in their area." Their research in financial markets indicated that firms in polluting industries tend to underperform compared to firms in sustainable industries during unusually warm periods.

Our objective is to replicate their methodology to compare results and critically evaluate their conclusions.

First, we show that attention to global warming, measured using Google Trends as a proxy, increases significantly during periods of abnormally high temperatures. This correlation seems particularly strong during extreme temperature anomalies, indicating heightened public concern. It is however not as strong as the result found by Choi et al [1].

Next, we analyze the correlation between abnormal temperatures and financial markets, employing a long-short portfolio strategy contrasting major emitting industries with others. Our findings indicate that during unusually warm periods, firms in polluting industries significantly underperform relative to those in more sustainable industries. This effect is not always most pronounced in the highest temperature quintiles.

Finally, we present additional analyses relevant to the study of this mechanism. Our rolling regression analysis shows that the correlation between abnormal temperatures and stock returns was significant up to 2017, but this significance diminishes in recent years, indicating changing market dynamics. Geographically, the results are mixed, with Europe showing slightly negative coefficients and Asia showing positive ones, though these patterns are not robust.

Gabriel Hayoun is an engineer from ISAE-SUPAERO, majoring in Data Science, and currently enrolled in the International Finance Major at HEC Paris. He will be joining BCG X as a data consultant.

Edouard Lelandais is an engineer graduated from ISAE-SUPAERO in fluid mechanics, with a dual degree from HEC Paris in the International Finance Major. He will commence his career in the energy investment sector.

2 Methodology and results of article "Attention to Global Warming" by Choi, Gao and Jiang (2017)

The study investigates how individuals adjust their beliefs about climate change when exposed to abnormally high local temperatures. Utilizing international data from seventy-four cities with major stock exchanges, the research leverages Google search volume as a proxy for public attention to climate change. It is observed that during periods of unusually high temperatures in a particular location, there is a significant increase in searches for "global warming" in that location, particularly when the temperatures are in the city's top quintile. This suggests that extreme weather events serve as "wake-up calls," prompting people to seek more information about climate change.

In the financial markets, the study examines the performance of stocks based on the pollution of their industry. Firms are categorized into high-emission and low-emission groups according to their industry, using industry classifications from IPCC reports. The findings reveal that during abnormally warm months, stocks of carbon-intensive firms significantly underperform compared to those of more sustainable firms. This underperformance is more pronounced when local temperatures are in the highest quintile.

The study further identifies that retail investors, rather than institutional investors or local blockholders, are responsible for the observed trading patterns. Retail investors tend to sell shares of high-emission firms and buy shares of low-emission firms during warmer periods, driven by heightened awareness of climate risks. This behavior indicates that individual investors react more strongly to salient, attention-grabbing weather events.

In summary, the research demonstrates that local abnormal temperatures not only increase public attention to climate change but also affect stock market dynamics by influencing the trading behavior of retail investors. This underlines the role of personal experience and limited attention in shaping collective beliefs and actions related to global warming. The methodology and results discussed above will be further explained and detailed in the following paper.

3 Data

This study utilizes monthly data from major cities around the world, specifically chosen based on the presence of significant stock exchanges. This selection, consistent with the work of Choi, Gao, and Jiang, includes 74 cities across Asia, Africa, Europe, North and South America, and Oceania. The rationale behind this selection is that cities with major stock exchanges are influential financial hubs where numerous investors are located, and local stock prices are partially influenced by these local investors (see, Chan, Hameed, and Lau (2003) [3]).

3.1 Temperature Data

Following Choi, Gao, and Jiang, we employ the Global Surface Summary of the Day (GSOD) data provided by the National Centers for Environmental Information (NCEI). This dataset includes daily observations of temperature, precipitation, snow depth, wind speed, and cloudiness from approximately 9000 stations globally, starting from around 1973 (though not all stations have data for the entire period). To associate a station with its respective city, Choi et al. used geographic coordinates to find the nearest station. However, many stations within cities have shorter time series. Consequently, we opted to use stations located at the international airports of these cities, as they typically have more extensive data coverage. While there may be minor temperature differences, the abnormal temperature metric we focus on—the deviation from the local seasonal norm—is expected to be similar between a city and its nearby airport.

The data is organized in the online database by year, with each year's folder containing approximately 9000 CSV files named by station ID, each file holding daily data for the year for a particular station. We collected this data using a Python script that constructs and requests the corresponding URL for each year and station. A manually created file, *data/temp/list_stations.csv*, lists the 74 stations of interest matched to their city names, selecting international airport stations as mentioned above. The script then merges all yearly files per station, and subsequently, all station files into a single CSV file. Daily data are averaged to obtain monthly temperatures for each station.

For the main study, data is available up to 2017, corresponding with the publication year of Choi et al.'s work. Their study period on financial markets spans from January 2001 to December 2017. Since seasonal norms are calculated over ten years, we require temperature data from January 1991 onward. Additionally, we downloaded data from 1973 to analyze long-term temperature trends, extending the dataset to December 2023 for a more comprehensive analysis.

Abnormal temperature is calculated as follows:

$$Ab\_Temp_{it} = Temp_{it} - Aver\_Temp_{it} - Mon\_Temp_{it} \quad \text{for city } i \text{ and month } t \tag{1}$$

Where:

$$\begin{cases} Ab\_Temp_{it} : \text{Abnormal temperature in city } i \text{ in month } t \\ \\ Temp_{it} : \text{Temperature in city } i \text{ in month } t = \frac{1}{|d_t|}\sum_{d_t} Temp_{d_t i} \ (d_t = \text{days of month } t) \\ \\ Aver\_Temp_{it} : \text{Average monthly temperature over the past 120 months in city } i \\ \\ Mon\_Temp_{it} : \text{Average deviation of month } t \text{ from average : Average temperature in} \\ \text{city } i \text{ in the same calendar month as } t \text{ over the past 10 years minus } Aver\_Temp_{it} \end{cases}$$

For some cities, we lack ten years of temperature data prior to 2001, resulting in the exclusion of certain data points at the beginning of the period, as Aver_Temp and Mon_Temp are calculated as rolling averages with a minimum period of ten years. The file used by Choi et al. in their study, containing temperature data from January 1983 to December 2017 for the 74 cities, is located at *data/temp/ab_temp.csv*. This file is used for regressions up to 2017 in this thesis to closely align with their article. For analyses extending up to 2023, we use the file *data/temp/ab_temp_to_2024.csv*, created with the described method.

3.2 Google Search Volume Index Data

To gauge investors' attention to global warming, we utilize the Google Search Volume Index (SVI) data from the Google Trends tool as a proxy for awareness. The assumption is that increased public concern about global warming correlates with higher search frequencies for the term "global warming" on Google.

The original dataset, spanning from 2004 (the inception of Google Trends) to December 2017, includes monthly SVI data for the 74 cities and/or their respective countries. Due to frequent unavailability of city-level data, Choi et al. often substituted country-level data. Hence, we decided to exclusively use country-level data and extend it up to December 2023.Data was downloaded using Pytrends, an unofficial Python API for Google Trends.

The SVI, scaled between 0 and 100, is transformed to compute the log monthly change ($DSVI$) for each month t in each country i, adjusted for seasonality:

$$DSVI_{it} = \log\left(\frac{SVI_{it}}{SVI_{i,t-1}}\right) - \text{Avg}_{\text{month } t \text{ over 2004-2023}}\left(\log\left(\frac{SVI_{it}}{SVI_{i,t-1}}\right)\right) \quad \text{for country } i \text{ and month } t \tag{2}$$

The data is provided in the file *data/gtrend/global.csv*.

3.3 Stock data

Datastream: The authors use Datastream data available from Thomson Reuters Refinitiv, that covers 100k+ equities.

Compustat: We had no access to Datastream, but had access to Wharton Research Data Service (WRDS) which provides the Compustat database.

- **Compustat database** is divided into a US/Canada database with 80k companies, and a Global database (world except US and Canada) with 33.9k companies.

- WRDS allows to request csv files from the database. We requested the following databases:

- **Compustat/North America/Securities Monthly** → *data/stocks/us.csv*

  Period: Jan-1983 to Dec-2023

  * `gvkey`: Global Company Key
  * `iid`: Issue ID
  * `datadate`
  * `tic`: Ticker Symbol
  * `prccm`: Price - Close - Monthly
  * `trt1m`: Monthly Total Return
  * `cshom`: Shares Outstanding Monthly - Issue
  * `exchg`: Stock Exchange Code
  * `gind`: GIC Industries

- **Compustat/Global/Securities Monthly** → *data/stocks/global_sm.csv*

  Period: Jan-2005 to Dec-2023 (maximum available)

  * `gvkey`: Global Company Key
  * `iid`: Issue ID
  * `datadate`
  * `ajpm`: Cumulative Adjustment Factor - Pay Date - Monthly
  * `prccm`: Price - Close - Monthly
  * `exchg`: Stock Exchange Code

- **Compustat/Global/Fundamentals–Annual** →

  data/stocks/global_fundamentals_annual.csv

  Period: Jan-2005 to Dec-2023 (maximum available)

  * `gvkey`: Global Company Key
  * `fyear`: Data Year - Fiscal
  * `datadate`
  * `cshoi`: Com Shares Outstanding - Issue
  * `gind`: GIC Industries

For the Global databases, the industry code $gind$ used for the long-short portfolio constitution and the number of shares outstanding used for market capitalization computation is provided in a separate database "Fundamentals – Annual" on an annual basis. The $gvkey$ is used as an identifier of companies to merge the "Global/Securities monthly" and "Global/Fundamentals – Annual" databases.

Moreover, Global database only provides monthly close price, whereas US database directly provides monthly returns.

We compute monthly returns for global with the following for stock i (each class of share of a company (represented by iid is considered as a unique company) in month t:

$$Mon\_Return_{it} = \frac{\frac{prccm_{it}}{ajpm_{it}}}{\frac{prccm_{i,t-1}}{ajpm_{i,t-1}}} - 1 \tag{3}$$

Where:

$$\begin{cases} prccm_{it} : \text{Price - Close - Monthly for share } i \text{ in month } t \\ \\ ajpm_{it} : \text{Cumulative Adjustment Factor - Pay Date - Monthly for share } i \text{ in month } t \end{cases}$$

We winsorize returns at the top and bottom 2.5% in each exchange in each month, according to the authors methodology. This means that top and bottom 2.5% values are set equal to the value of the 2.5^{th}% quantile. This narrows down outliers' value without deleting data points like a trimming would do. Market capitalization for company i in month t is calculated as monthly close price times number of shares outstanding (monthly available for US, annually available for Global). Finally, Compustat gives an exchange code $exchg$. WRDS provides a table linking these exchange codes with the exchange name and the country of the exchange. We filter the table to keep only the countries of interest in the study and added by hand the city of the exchange next to the exchange code. This is provided in the file *data/stocks/exchange_code_table_final.xlsx.*

We compute size-adjusted returns for each firm. Adjusted returns equal raw returns minus the average return of stocks in the same size quintile by each city. This is a way to get rid of the size effect in the panel. It is as if we added a size factor further in our regression, but instead we deduct the size effect beforehand in the regressand.

city	country	Continent	Firms_Article	Firms_Thesis
Amman	Jordan	Asia	228	232
Amsterdam	Netherlands	Europe	247	195
Athens	Greece	Europe	364	284
Bangkok	Thailand	Asia	796	1190
Berlin	Germany	Europe	54	46
Bern	Switzerland	Europe	18	28
Bogota	Colombia	SouthAmerica	74	78
Bratislava	Slovakia	Europe	25	17
Brussels	Belgium	Europe	280	216
Bucharest	Romania	Europe	272	149
Budapest	Hungary	Europe	77	51
Buenos Aires	Argentina	SouthAmerica	97	94
Busan	South Korea	Asia	1006	2160
Cairo	Egypt	Africa	198	211
Colombo	Sri Lanka	Asia	294	308
Copenhagen	Denmark	Europe	285	229
Dhaka	Bangladesh	Asia	410	292
Dublin	Ireland	Europe	76	69
Dusseldorf	Germany	Europe	58	23
Frankfurt	Germany	Europe	1735	1816
Hamburg	Germany	Europe	65	71
Hanoi	Vietnam	Asia	400	237
Harare	Zimbabwe	Africa	71	58
Helsinki	Finland	Europe	208	203

city	country	Continent	Firms_Article	Firms_Thesis
Ho Chi Minh	Vietnam	Asia	340	327
Hong Kong	Hong Kong	Asia	2064	1735
Istanbul	Turkey	Europe	461	401
Jakarta	Indonesia	Asia	592	567
Johannesburg	South Africa	Africa	663	493
Karachi	Pakistan	Asia	410	466
Kiev	Ukraine	Europe	83	38
Kuala Lumpur	Malaysia	Asia	1207	1187
Kuwait	Kuwait	Asia	177	209
Lagos	Nigeria	Africa	160	174
Lima	Peru	SouthAmerica	140	141
Lisbon	Portugal	Europe	97	68
Ljubljana	Slovenia	Europe	137	40
London	United Kingdom	Europe	3558	5365
Luxembourg	Luxembourg	Europe	38	37
Madrid	Spain	Europe	298	268
Manila	Philippines	Asia	283	308
Mexico City	Mexico	NorthAmerica	183	246
Milan	Italy	Europe	519	500
Moscow	Russia	Europe	349	533
Mumbai	India	Asia	4806	3999
Munich	Germany	Europe	90	49
Muscat	Oman	Asia	98	112
Nagoya	Japan	Asia	116	76
New York City	United States	NorthAmerica	3874	9078
Nicosia	Cyprus	Europe	143	78
Osaka	Japan	Asia	140	62
Oslo	Norway	Europe	446	371

city	country	Continent	Firms_Article	Firms_Thesis
Paris	France	Europe	1578	987
Prague	Czech Republic	Europe	71	33
Riyadh	Saudi Arabia	Asia	182	189
Santiago	Chile	SouthAmerica	236	235
Sao Paulo	Brazil	SouthAmerica	297	666
Shanghai	China	Asia	1180	1448
Shenzhen	China	Asia	2024	2118
Singapore	Singapore	Asia	920	972
Skopje	Macedonia	Europe	40	0
Sofia	Bulgaria	Europe	157	102
Stockholm	Sweden	Europe	1102	834
Stuttgart	Germany	Europe	55	83
Sydney	Australia	Oceania	2888	2569
Taipei	Taiwan	Asia	1023	2182
Tel Aviv	Israel	Asia	785	498
Tokyo	Japan	Asia	3656	4003
Toronto	Canada	NorthAmerica	841	5254
Vienna	Austria	Europe	166	179
Warsaw	Poland	Europe	1075	967
Wellington	New Zealand	Oceania	229	208
Zagreb	Croatia	Europe	73	103
Total			**49819**	**62206**

Table 1: Comparison of number of firms in the 74 cities of the study between the article (Datastream data) and our thesis (Compustat data)

Industry classification – Emission minus Clean portfolio:

To evaluate the impact of abnormal temperatures on financial markets, the authors chose to constitute two portfolios: Emission and Clean. Emission portfolio is constituted of firms in industries identified as major emission sources by the Intergovernmental Panel on Climate Change (IPCC): Energy, Transport, Buildings, Industry, Agriculture Forestry and Other Land Use (AFOLU). They matched by hand the industry names provided by Datastream with the IPCC subcategories of these 5 sectors, available in the Annex II of the IPCC's Fifth Assessment Report, issued in 2014 (Krey et al. (2014), P.1302–1304 [4]). The matching table they produced is available in Table IA.1 in the Internet Appendix of the original article. Using Compustat data, we have not access to the proprietary industry names of Datastream. Thus, we decided to use a more standardized approach using a non-proprietary industry classification. We used the Global Industry Classification Standards (GICS) by MSCI, which is provided by Compustat.

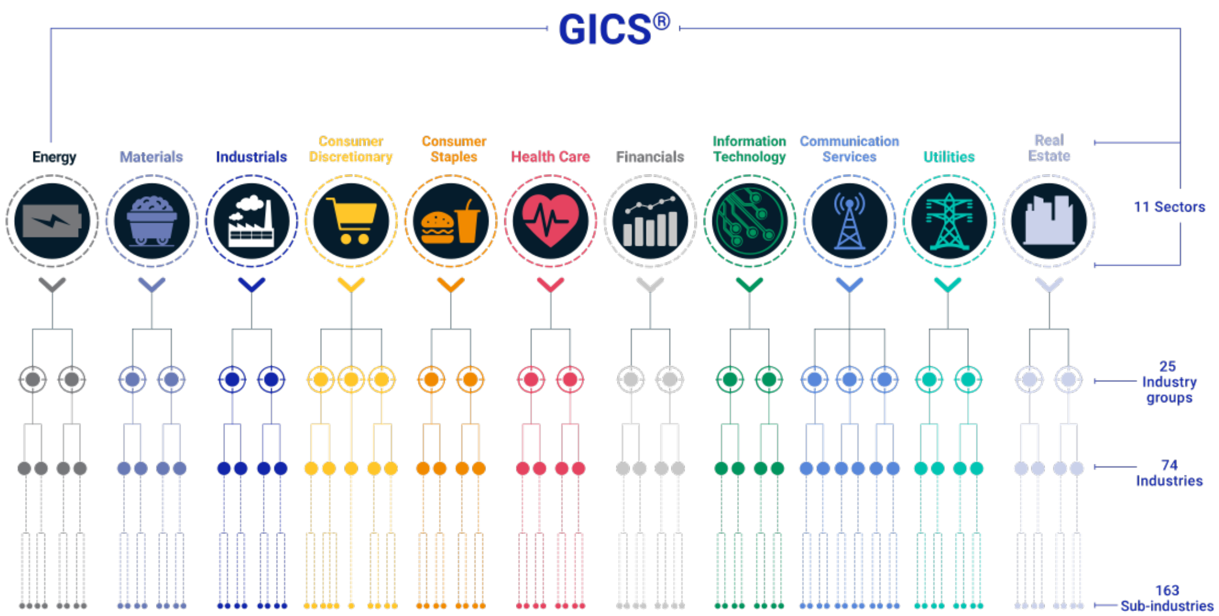


Figure 1: Global Industry Classification Standards by MSCI

Out of this 4-level classification, we decided to use the Industry level (74 Industries), which seemed to be granular enough and quite similar in comparison with Datastream industry names. We matched by hand these GIC codes to a dummy variable that equals 1 when the industry is similar to the one selected by the authors as polluting (namely corresponds to IPCC sub-categories), and 0 otherwise. This is provided in the file *data/stocks/GICS Map 2023.xlsx*, and visible in Table 5 in Appendix 9.1.

All the stocks data is combined in the file *data/stocks/stocks_wrds_global_us.csv*. Emission and Clean portfolios are constituted according an equal weight or market capitalization weight of returns. For each location (city or country) i, firms with an emission dummy equal to 1, belong to portfolio Emission. All other firms belong to the Clean portfolio.

Then we long portfolio Emission and short portfolio Clean. The return of this portfolio "emission minus clean" for month t in city or country i is:

$$EMC_{it} = EMISSION_{it} - CLEAN_{it} \tag{4}$$

We use raw returns and size-adjusted returns. Raw returns'-based portfolios are referred to as $EMC(raw)$, adjusted returns'-based as EMC.

4 City temperature and global warming

The temperature data in each of the 74 cities of the study allows to clearly see an increase in temperature.

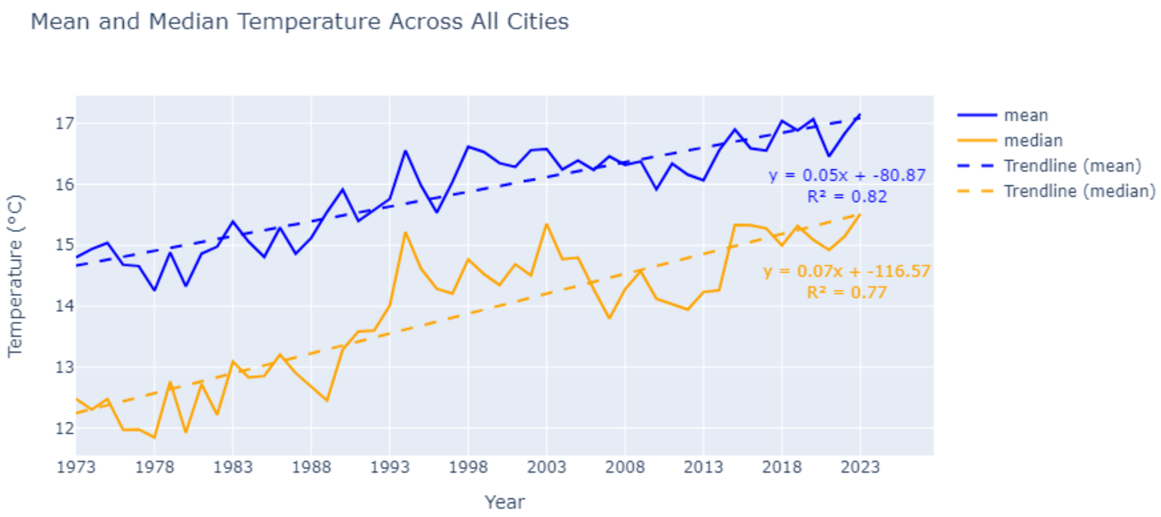


Figure 2: Evolution of mean and median annual temperature across 74 cities worldwide over the period 1973-2023

These 74 cities have warmed up 2.4°C on average over 50 years. The linear regression on mean annual temperatures, shown in Figure 2, gives a coefficient of 0.05°C/year (hence the 2.4°C over 50 years). The fitting of a linear trend on the evolution of annual temperatures is impressive, with an R-squared of 0.82 for the mean across cities.

It confirms the relevancy of using cities' temperatures in a study of attention to global warming, since clearly from this graph, inhabitants of these big 74 cities have suffered from a local increase in temperature.

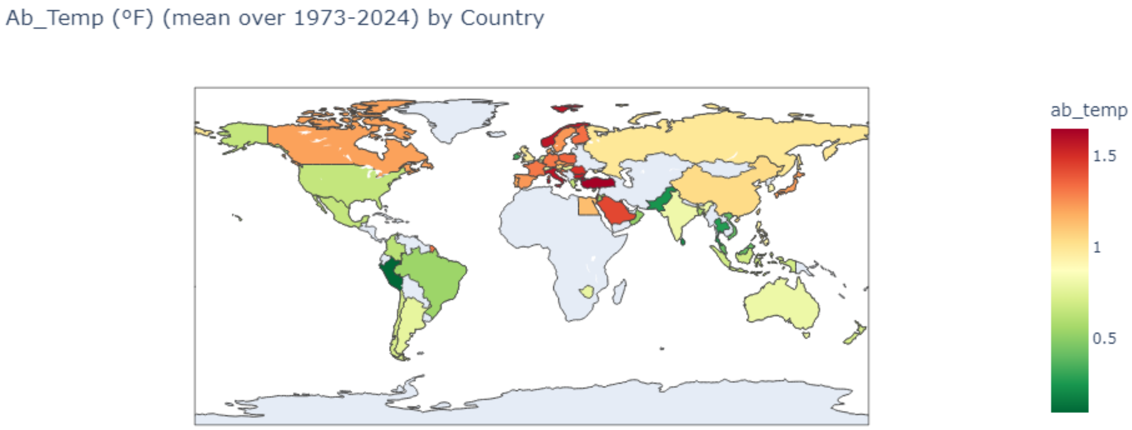


Figure 3: Mean abnormal temperature of 74 cities (displayed as countries)

Abnormal temperatures are positive on average in each city as shown on Figure 3. Moreover, northern hemisphere cities appear to have higher abnormal temperatures over the period, especially in Europe.

All cities' inhabitants are not subject to the same amplitude of effect of global warming, which adds to the diversification of the panel.

5 Global Methodology

The aim of this paper is to ascertain the correlation, if any, between a variable (referred to as y) and abnormal temperatures. The variable can be google search volume index change, stock returns...

5.1 Linear Regression

The primary analysis employs the following panel regression model:

$$y_{it} = \alpha + \beta Ab\_Temp_{it} + \sum_t YearMonth_t + \epsilon_{it} \qquad \text{for city/country } i \text{ and month } t \tag{5}$$

Regression can be computed at city level or at country level. In the case of country level, abnormal temperatures of cities in the country are averaged, size-adjusted returns of firms are computed on size-quintiles of firms in the country, and emission/clean portfolios are constituted at the country level.

In Equation 5, the $YearMonth$ effect is computed using dummy variables for each combination of year and month. This approach ensures that any systematic variations in the dependant variable y over time are properly accounted for. Time-fixed variable captures the change that is common to all cities/countries in month-year t. This strengthens the focus of the study on geographical variation. We examine the correlation between y and abnormal temperatures in cities/countries when they have higher abnormal temperatures than other location in a given month.

Our coefficient of interest is β. In addition to the linear regression utilizing the abnormal temperature variable (Ab_Temp_{it}), we further categorize all months into quintiles based on Ab_Temp_{it} within each city i, assigning quintile dummies accordingly. Subsequently, these quintile dummies are employed in the regression analysis in lieu of the continuous abnormal temperature variable.

This approach allows for a more nuanced examination of the relationship between temperature anomalies and public attention to global warming by discerning potential differences in attention across quintiles of abnormal temperatures. By considering quintiles, we capture not only the linear effect of abnormal temperatures but also potential non-linearities or threshold effects that may influence public perception and engagement with climate-related issues.

5.2 Rolling Linear Regression

A rolling linear regression is conducted over 10-year periods, spanning from 2001-2011 to 2013-2023. This approach serves two purposes: first, it provides a robustness analysis by conducting multiple regressions instead of a single one; second, it facilitates an examination of potential changes in coefficients and t-statistics over time. It allows to show as well the extension of the study to a broader period, namely with the years 2017-2023 that were not covered in Choi et al.'s article.

5.3 Linear Regression by country

A time-series regression is ran for each country, in order to analyze geographical specificities and test robustness by looking at consistency of results worldwide. Thus we get a β coefficient per country. This section introduces a finer granularity to the analysis by accounting for geographical distinctions at the country level.

A separate regression is conducted for each country using the following model:

$$y_t = \alpha + \beta Ab\_Temp_t + \sum_t YearMonth_t + \epsilon_t \qquad \text{for month } t \tag{6}$$

The analysis not only provides insights into the relationship between the variable of interest (and abnormal temperatures (Ab _Temp) but also allows for an examination of robustness across different countries. Consistency in results across a majority of countries would lend further credence to the findings and highlight broader patterns in the data.

6 Attention and local temperatures

6.1 Methodology

To investigate the relationship between heatwaves and public attention to global warming, the Google Search Volume Index (SVI) of expression "global warming" was used as a proxy for public interest and engagement. The methodology focused on capturing changes in attention over time and across different geographic locations.

The first step involved calculating the logarithm of the monthly change in SVI, denoted as $DSVI$, for each country in the study. This metric allowed for the quantification of fluctuations in public interest in global warming over time. Taking the logarithm of the change ensured that the analysis was sensitive to both increases and decreases in attention while mitigating the influence of extreme outliers.

Furthermore, to account for any inherent seasonality in search behavior, the $DSVI$ values for each country were adjusted to remove any regular patterns that might obscure the true relationship between heatwaves and attention to global warming. This adjustment was achieved by subtracting the $DSVI$ by the average $DSVI$ for each country and month. The results are then winsorized at the top and bottom 2.5% tails.

Subsequently, the adjusted $DSVI$ values were juxtaposed with local temperature data to explore potential correlations between heatwaves and changes in public attention.

6.2 Results and comparison to the original paper

Table 2a presents the summary statistics for $DSVI_{it}$, as well as for $Aver\_Temp_{it}$, Mon_Temp_{it}, and Ab_Temp_{it}.

The findings closely mirror those of the original paper, with the mean of $DSVI(country)$ of -1.349 close to zero as in the article, yet negative on the contrary to the article. The mean values for Ab_Temp of 0.310°F is close to the 0.256°F of the authors. We have less observation (7656 vs 10366) essentially because we have 59 countries vs 63, because of lack of google trend data.

One notable discrepancy lies in the standard deviation of $DSVI$, which is halved compared to the original paper (29 compared to 66). A closer examination of the percentile values reveals that the most significant disparities occur at the lower and higher ends of the distribution. For instance, the 10th percentile (P10) is -38 compared to -58, and the 90th percentile (P90) is 35 compared to 59.

The reasons behind these data differences can only be hypothesized, given that the original dataset is unavailable. One possible explanation is that our dataset was aggregated at the country level, as opposed to the original paper's city-level granularity. Moreover, Google Trend is known for changing its normalization methodology and volume index computation frequently, thus we cannot reproduce the data they used in 2017.

Table 2b displays the outcomes of the linear regression of $DSVI$ against abnormal temperature, as referenced in Equation 5. Notably, the results diverge significantly from those reported in the original paper.

An initial observation reveals that none of the coefficients (neither on Ab_Temp nor on quintile dummies of Ab_Temp) reach statistical significance. Consequently, drawing definitive conclusions from this analysis is challenging. This outcome is indeed disappointing.

In contrast to the original paper, where the coefficient estimate of Ab _Temp exhibited significant positivity (t-stat = 2.26), indicating heightened public attention to global warming during periods of abnormal high temperatures, no such confirmation or refutation can be made based on our findings.

However, it is worth noting that despite the lack of statistical significance, the positive coefficient estimate on Ab_Temp (0.097) suggests a plausible relationship between abnormal temperatures and public attention to global warming. But this coefficient is not far enough from 0 with respect to the standard deviation to interpret anything.

When examining the regression results that are statistically insignificant based on temperature quintiles, we cannot conclude on any impact of warmer months on public interest in global warming tends to intensify during periods characterized by more extreme abnormal temperatures.

The expected outcome was that individuals would exhibit greater interest on google in global warming during periods of more pronounced temperature anomalies. But based on the low t-statistics, we fail to reject this null hypothesis.

Table 2: Google search volume for “global warming” and abnormal temperature

(a) Summary Statistics

Variable	Obs	Mean	SD	P10	P25	P50	P75	P90
DSVI (country)	7656	-1.349	28.969	-38.259	-18.116	-1.116	16.053	34.640
Aver_Temp	7656	62.255	12.609	47.869	51.810	59.932	72.192	82.089
Mon_Temp	7656	-0.479	10.331	-15.053	-7.922	0.026	6.066	13.730
Ab_Temp	7656	0.310	2.597	-2.608	-1.076	0.282	1.673	3.354
# Exchange countries	59							

(b) Regression of DSVI on abnormal temperature

	(1) DSVI (country)	(2) DSVI (country)
Ab_Temp	0.097	
	(0.799)	
Ab_Temp Q2		-0.371
		(-0.392)
Ab_Temp Q3		-1.121
		(-1.180)
Ab_Temp Q4		-1.159
		(-1.215)
Ab_Temp Q5		0.053
		(0.055)
Obs	7656	7656
Adj. R2	0.225	0.225

Visually, no clear trend emerges between the two variables, as illustrated in Figure 4 and 5. Currently, the correlation between attention to global warming and abnormal temperature appears lukewarm at best. Given this, it's uncertain whether it will have any significant impact on the stock market.

Figure 4: $DSVI$ against Ab_Temp on a random 15% sample of the data

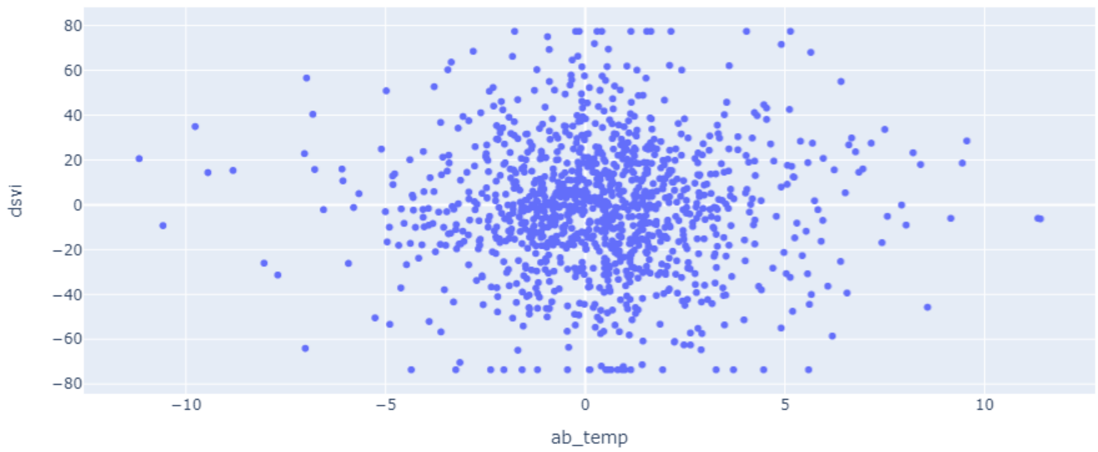
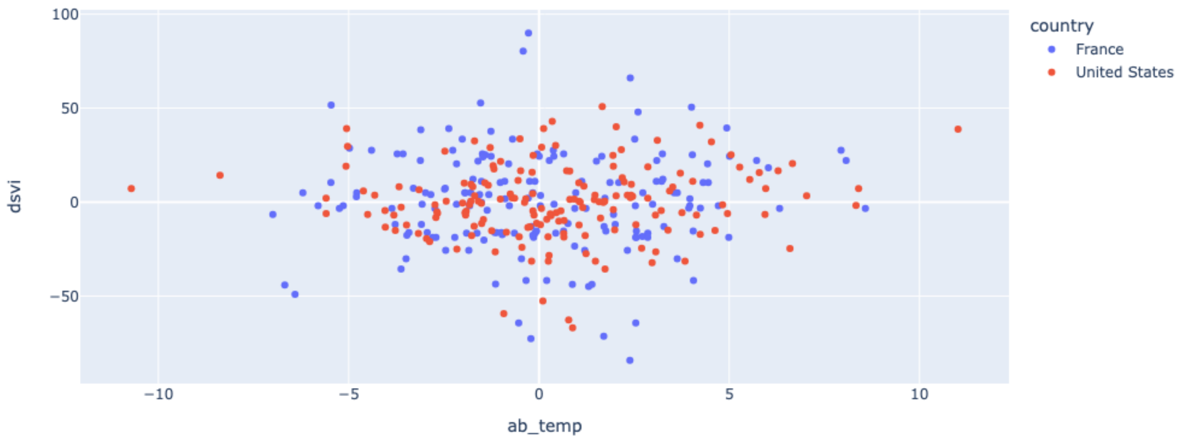


Figure 5: $DSVI$ against Ab_Temp for France and the US



6.3 Results with extension of data to 2023

We extended the Google Trend data and temperature data up to December 2023 and ran the same regression as above.

Table 3: Google search volume for "global warming" and abnormal temperature

(a) Summary Statistics

Variable	Obs	Mean	SD	P10	P25	P50	P75	P90
DSVI (country)	9794	-0.673	30.833	-40.404	-18.263	-0.733	17.145	37.840
Aver_Temp	9794	61.519	12.942	48.166	51.306	58.138	73.296	82.090
Mon_Temp	9794	-1.221	10.577	-15.915	-9.350	-0.729	6.607	13.183
Ab_Temp	9794	1.297	2.517	-1.512	-0.153	1.158	2.723	4.410
# Exchange countries	56							

(b) Regression of DSVI on abnormal temperature

	(1) DSVI (country)	(2) DSVI (country)
Ab_Temp	0.225**	
	(2.001)	
Ab_Temp Q2		-1.171
		(-1.395)
Ab_Temp Q3		-0.797
		(-0.941)
Ab_Temp Q4		-0.397
		(-0.466)
Ab_Temp Q5		0.519
		(0.602)
Obs	9794	9794
Adj. R2	0.322	0.322

Despite the $DSVI$ distribution not changing much when the period was expanded, the abnormal temperatures have increased. Mean abnormal temperature increases from 0.310°F in 2004-2017 period to 1.297°F in the extended 2004-2023 period. So there are more abnormally warm data points. Moreover, the number of observations is obviously increased.

Table 3b displays the outcomes of the linear regression of $DSVI$ against abnormal temperature, as referenced in Equation 5. Notably, these results align more closely with those reported in the original paper than the previous analyses.

Expanding the period of the dataset reveals that the coefficient on Ab_Temp reaches statistical significance. This suggests that attention to global warming is indeed correlated with abnormal temperatures.

When examining the regression results based on temperature quintiles, the statistically insignificant results prevent a definitive conclusion about the impact of warmer months on public interest in global warming. However, there is a notable trend: public interest tends to intensify during periods characterized by more extreme abnormal temperatures, as the higher β coefficient on Ab_Temp $Q5$ suggests.

The expected outcome was that individuals would exhibit greater interest in global warming on Google during periods of more pronounced temperature anomalies. Although the increase in the coefficient between $Q4$ and $Q5$ is significant, suggesting stronger attention during periods of more extreme temperatures, the overall findings are not conclusive.

7 Stock returns and local temperatures

7.1 Methodology

This study examines whether local temperature affects stock prices, focusing on different reactions among firms based on their greenhouse gas emissions. Firms are divided into high and low emission groups based on their industry. High-emission firms are those in industries identified by the IPCC as major emission sources. These firms are more sensitive to climate change because higher production costs, stricter environmental regulations, or avoidance by socially responsible investors can affect their future cash flows.

To analyze this, two portfolios are created based on the IPCC definitions. In each city i from 2001 to 2017 (or 2023), the portfolio $EMISSION_i$ includes all firms in industries mapped to IPCC polluting sectors. All other firms in city i are placed in the $CLEAN_i$ portfolio. A long-short portfolio EMC_i (Emission Minus Clean) is then formed by buying $EMISSION_i$ and selling $CLEAN_i$. Both equal-weighted and value-weighted portfolios are constructed.

Raw returns are adjusted by winsorizing the top and bottom 2.5% each month in each exchange, and returns above 300% are trimmed to remove extreme outliers. These raw returns are then converted to size-adjusted returns. The size-adjusted return is defined as the stock return minus the average return of stocks in the same size quintile within the exchange for the same month.

7.2 Results and comparison to the original paper

In order to compare our results with the paper, this part contains only data from 2001 to 2017 (the same period as the original paper).

The dataset used in this study differs significantly from the original paper, particularly concerning returns and the resulting EMC, $EMISSION$, and $CLEAN$ portfolios. Let's look at summary statistics for equal weighted portfolios, presented in Table 4a.

EMC and $EMC(raw)$ have mean values close to zero, similar to the original paper. $EMISSION$ and $CLEAN$ portfolios have mean returns near 0.9% notably higher than for the portfolios formed by Choi.

For the EMC portfolios, notable differences are observed in the standard deviation and the overall data distribution. The standard deviation in our dataset is much smaller (~2% compared to ~5% in the original paper). Additionally, the 10th percentile (P10) is lower (-1.1% compared to -3.5%), as is the 90th percentile (P90) (1.1% compared to 3.8%). Unlike the original data which shows a slight skewness toward positive values, our dataset does not exhibit this skewness.

For the $EMISSION$ and $CLEAN$ portfolios, the opposite trend is evident. The standard deviation is significantly higher (~9% compared to ~2-3% in the original paper), and the data distribution is much broader in our case.

The same methodology was employed to clean the data, trim and winsorize returns. The differences in the data can likely be attributed to the different data sources used, which may have resulted in the inclusion of different companies, indeed we have more companies 62k vs 50k, as visible in Table 1. We have slightly less observations than them (10976 vs 12614) due to possible different availability of returns for some cities in the Compustat database. Let's remind that Compustat Global database (all countries outside of US and Canada) starts in January 2005.

Moreover, since we couldn't access the proprietary Datastream industry codes and use their matching table to emission sectors, we tried to replicate at best using Global Industry Classification Standards but eventually might have some disparities in the classification of firms as part of $EMISSION$ portfolio or $CLEAN$ portfolio.

Panels 4b (equal-weighted) and 4c (value-weighted) present the regression results. Column 1 of Panel B shows that higher abnormal temperatures are associated with significantly lower EMC size-adjusted returns. A 1-standard-deviation increase in Ab_Temp corresponds to a decrease of 6 basis points in EMC return ($= -0.021 \times 2.822$) for the equal-weighted portfolio.

For both equal-weighted and value-weighted portfolios, the results for the EMC portfolios (with size-adjusted returns) are similar to those in the original paper and are statistically significant. The negative coefficient implies that in abnormally high temperatures, the emission minus clean long-short portfolio has negative return, in other words, when its abnormally warm, clean portfolio outperforms emission portfolio.

However, the results for the non-adjusted EMC (referred to as $EMC(raw)$) are not statistically significant, which differs from the original paper. This discrepancy may be due to the difference of database or to the difference in portfolios constitution (industry classification).

Column 2 replaces Ab_Temp with quintile dummies based on the city's abnormal temperature. For the equal-weighted portfolio, there is no significant difference in effects between the quintiles, indicating no substantial non-linear effects. This is consistent with the conclusions drawn from our previous Google SVI results.

For the value-weighted portfolios, the negative effect on EMC returns is the strongest in the highest temperature quintile. The economic impact is significant, with a change from temperature quintile 1 (coolest) to quintile 5 (warmest) corresponding to a drop of 24 basis points (t-stat = -2.37) in size-adjusted return. This finding aligns with the original paper's results regarding the non-linear effects of abnormal temperature.

Finally, Columns 5 and 6 examine the size-adjusted returns for the EMISSION and CLEAN portfolios, respectively. Both returns are very close.

Figure 6 plots the average value-weighted EMC size-adjusted returns and the confidence intervals across five temperature quintiles in the exchange city. A general decrease in EMC returns is observed as the temperature quintiles increase, with statistically significant underperformance (negative return) in the warmest quintile. This result is confirming the findings of the original paper.

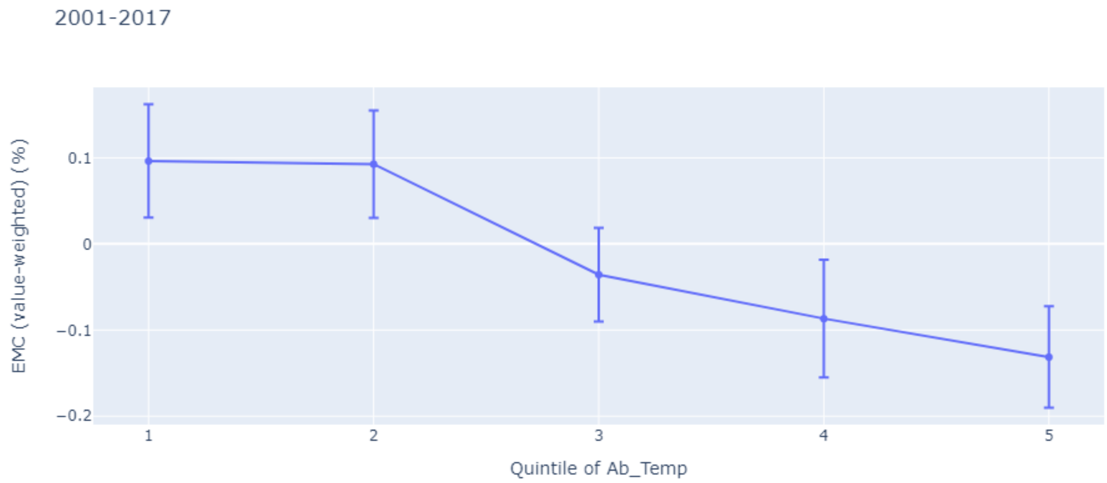


Figure 6: EMC (value-weighted) on abnormal temperature quintiles, 2001–2017
Error bars displays the 95% confidence interval, namely +- 1.96*standard deviation(EMC)

Table 4: Emission-minus-clean portfolio return and abnormal temperature

(a) Summary Statistics

Variable	Obs	Mean	SD	P10	P25	P50	P75	P90
Equal Weighted								
EMC	10976	0.019	1.960	-1.108	-0.376	0.009	0.445	1.120
EMC(raw)	10976	0.042	4.163	-3.483	-1.443	0.021	1.528	3.580
EMISSION	10976	0.892	9.041	-6.350	-2.462	0.669	3.846	7.770
CLEAN	10976	0.850	9.010	-5.747	-2.176	0.644	3.482	7.089
Value Weighted								
EMC	10976	-0.013	3.172	-2.253	-0.911	0.000	0.913	2.267
EMC(raw)	10976	0.184	6.455	-5.702	-2.350	0.119	2.699	6.024
EMISSION	10976	1.431	9.793	-6.033	-2.053	0.996	4.438	8.665
CLEAN	10976	1.248	9.447	-5.739	-1.969	0.913	3.979	7.868
Ab_Temp	10976	0.256	2.703	-2.833	-1.215	0.237	1.693	3.449

(b) Equal-weighted EMC returns

	(1)	(2)	(3)	(4)	(5)	(6)
	EMC		EMC (raw)		Emission	Clean
Ab_temp	-0.021***		-0.000		-0.048	-0.047
	(-2.822)		(-0.026)		(-1.498)	(-1.473)
Ab_temp Q2		-0.088		-0.068		
		(-1.440)		(-0.525)		
Ab_temp Q3		-0.126**		-0.209		
		(-2.047)		(-1.612)		
Ab_temp Q4		-0.182***		-0.106		
		(-2.944)		(-0.818)		
Ab_temp Q5		-0.120*		0.031		
		(-1.918)		(0.235)		
Obs	10976	10976	10976	10976	10976	10976
Adj. R2	-0.001	-0.002	0.015	0.015	0.171	0.152

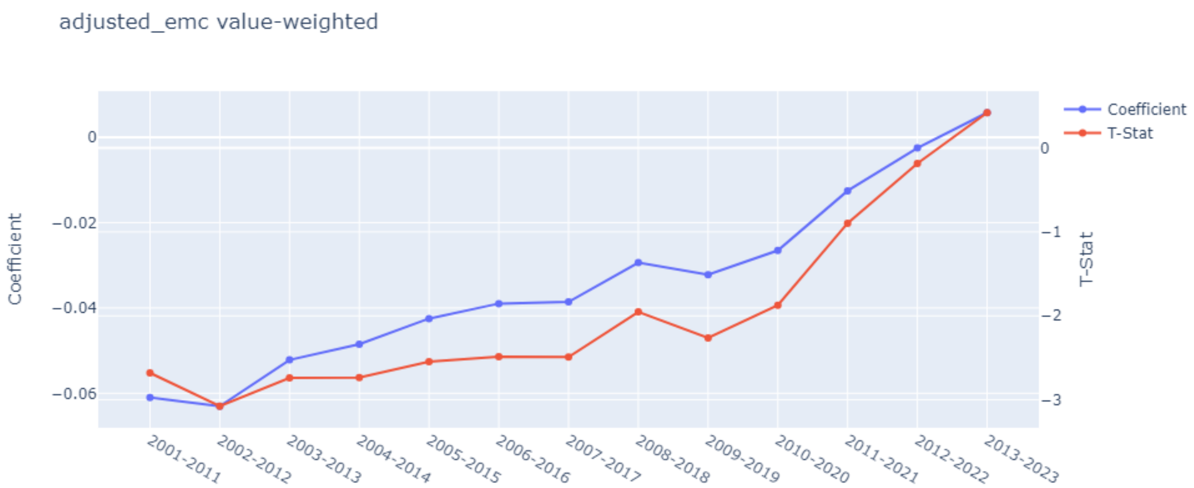
(c) Value-weighted EMC returns

	(1)	(2)	(3)	(4)	(5)	(6)
	EMC		EMC (raw)		Emission	Clean
Ab_temp	-0.041***		-0.010		-0.037	-0.027
	(-3.368)		(-0.424)		(-1.063)	(-0.789)
Ab_temp Q2		-0.024		-0.076		
		(-0.241)		(-0.382)		
Ab_temp Q3		-0.153		-0.209		
		(-1.534)		(-1.046)		
Ab_temp Q4		-0.192*		-0.287		
		(-1.917)		(-1.430)		
Ab_temp Q5		-0.240**		0.142		
		(-2.372)		(0.700)		
Obs	10976	10976	10976	10976	10976	10976
Adj. R2	-0.002	-0.002	0.025	0.025	0.147	0.141

7.3 Rolling linear regression

As stated previously, a rolling linear regression over time is used to test the robustness of the results and to observe any potential evolution over the years. This method involves running regressions over moving 10-year periods to ensure that the findings are not driven by a specific timeframe but are consistent across different periods.

Figure 7: *EMC* (value-weighted) on abnormal temperature on a 10-year rolling basis

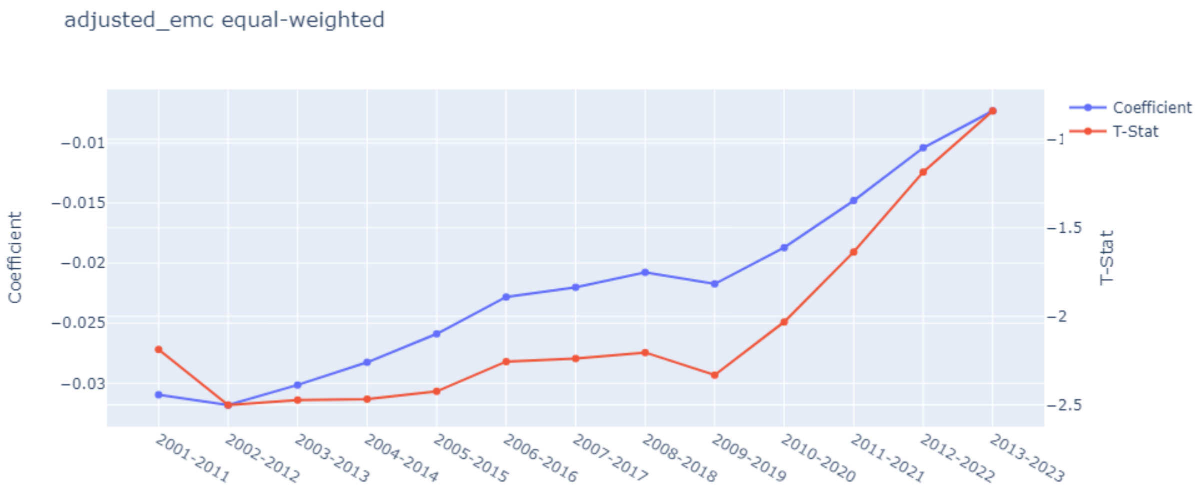


For the value-weighted portfolio, all results are statistically significant at the 99% confidence interval before 2017, then the confidence level is 95% for the periods 2006-2020, and starting from period 2011-2021, the t-stat become statistically insignificant. This consistency across multiple time frames enhances confidence in the robustness of the findings in early periods, indicating that there was indeed a correlation between stock returns of *EMC* portfolios and abnormal temperature between 2001 and 2017/2020. In period 2013-2023, the coefficient and t-stat are very close to 0, suggesting by the fail of rejection of the null hypothesis that there is no correlation anymore.

One hypothesis we can draw from this graph, even though it is just a conjecture given this information, is that since the article of Choi was published in 2017, the market arbitraged this correlation.

The upward trend of the coefficient through the year can also suggest a systematic change in the data, either in the abnormal temperatures or in the EMC portfolios.

Figure 8: EMC (equal-weighted) on abnormal temperature on a 6-year rolling basis



For the equal-weighted portfolio, conclusions are the same. The statistical significance, shown by the t-stat, is high (above 99 or 95%) up to period 2011-2021, and the coefficient is upward trending towards 0, with results becoming statistically insignificant from period 2012-2022. The graphs really look alike and displays the same upward trend throughout the years.

The effect is less pronounced for equal-weighted portfolios as seen previously in part 6.2. Indeed the coefficient of the regression β is -3bps at a minimum (period 2001-2011) at a t-stat of -2.3 whereas for value weighted portfolios, the β is -6bps for the same period, with a t-stat of -2.8. But the significance is more or less similar.

The value-weighted rolling linear regressions tend to revert to non-significant results more quickly than the equal-weighted regressions. This phenomenon might be linked to the fact that there are fewer arbitrage opportunities for larger companies, as the market more efficiently incorporates new information for these firms.

7.4 Linear Regression by country

The goal of this section is to determine if there is a geographical pattern in the relationship between abnormal temperatures and *EMC* returns, examining differences by continent and between northern and southern countries. This also serves as a robustness test to assess whether the findings hold at the country level, despite the reduced number of data points.

The results are somewhat disappointing, as only three countries show significant results at the 95% confidence interval. This lack of significance in most countries makes it challenging to draw strong conclusions from the analysis. Additionally, most countries have coefficients very close to zero, further complicating the interpretation of results.

However, if we attempt to discern a pattern, it appears that most countries in Europe exhibit negative coefficients, though these are generally very slight. Conversely, many countries in Asia show positive coefficients. Despite these observations, the overall lack of significant results suggests that geographical patterns are not robustly supported by the data.

The regression results by continent are summarized in the following table:

Continent (#)	Coefficient	Confidence
Africa (4)	0.169	0.55
Asia (22)	0.075	0.39
Europe (27)	−0.071	0.55
North America (3)	0.003	0.16
Oceania (2)	0.025	0.33
South America (5)	−0.156	0.50

These results provide insights into the relationship between abnormal temperatures and *EMC* returns across different continents. Notably, Asia and Africa show a positive coefficient indicating a potential positive impact of abnormal temperatures on *EMC* returns in this region. Conversely, Europe and South America exhibit a negative coefficient.

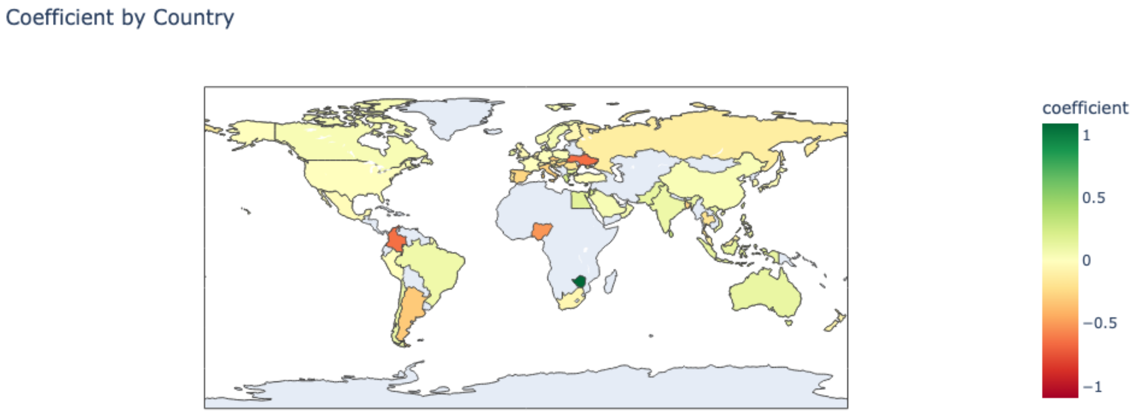


Figure 9: Coefficient β of regression of EMC on Ab_Temp per country

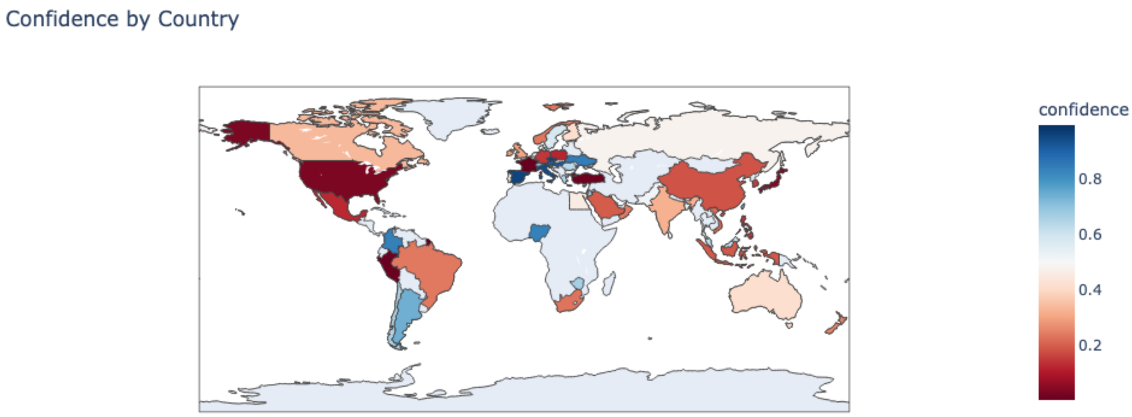


Figure 10: Confidence level of coefficient β on the null hypothesis per country

8 Critics and conclusions

8.1 Critique of Methodology

Investigating the impact of attention to global warming on stock markets is a complex task. The challenge lies in identifying the specific investors affected by global warming, determining their trading behaviors, and monitoring their trades. The authors of the original article chose to study a panel of cities with major stock exchanges, hypothesizing that these populous cities have a concentration of investors who exhibit a home bias by investing in local stocks.

We find this approach questionable. Firms listed on major stock exchanges are traded by investors worldwide, making it unlikely that returns are driven by the small fraction of investors residing in the city of the exchange. In order to verify this intuition, a new variable $Fraction\_Foreign\_Ownership$ could be introduced. An interaction term between Ab_Temp and $Fraction\_Foreign\_Ownership$ could be added in the regression model to verify a potential impact of this cross factor. A positive coefficient on this cross factor would indicate that EMC returns are less impacted by Ab_Temp when the fraction of foreign ownership of a stock is higher. Unfortunately, Compustat database does not include any ownership data, so we could not run this regression to verify this hypothesis.

Furthermore, if home bias is a supporting argument, it is unclear why only the temperature of the city of the exchange is considered, and not other cities in the country where investors could also experience heat waves at different times. Nevertheless, while the study set may not be comprehensive, it might still be relevant enough to detect a small correlation.

Another methodological point concerns the constitution of the EMC portfolios. While the long-short portfolio approach is standard and appears relevant, the criterion for categorizing firms as either emission or clean portfolios is debatable. The authors classified firms based on their industry, using an exclusion mechanism rather than a best-in-class approach. Although the intuition behind this is understandable, it is not clear if investors exclude the most polluting industries when rebalancing their portfolios based on updated beliefs about global warming.

The authors classified industries as polluting based on IPCC reports, which mention major emission sources. While this seems reasonable, it is not evident that investors read IPCC reports or identify Energy, Transport, Buildings, Industry, Agriculture, Forestry, and Other Land Use (AFOLU) as emitting sectors. Even if they do, it is uncertain whether they believe these sectors are problematic in relation to global warming. Some sectors, like oil, coal, and aviation, are notoriously emitting and face sustainability challenges, but not all major source emission industries are perceived similarly.

Google Trends data is another concern. Google has changed its index calculation methods and normalization processes multiple times, leading to potential inconsistencies. Therefore, we do not recommend using this data as a proxy for attention to global warming.

8.2 Critique of the Article's Form

Regarding the implementation of the methodology and the article itself, we have several comments to add depth to the conclusions.

First, the data is not verifiable, except for the abnormal temperature file. While the stock return database is licensed and cannot be provided in raw form, the authors could have provided the *EMC* portfolio returns per city and the Google Trends data they used.

Second, the authors did not provide any code or detailed their calculations. The computations and numerous adjustments made to the data are only briefly explained in plain English, leaving room for interpretation.

Lastly, data cleaning and pre-processing are crucial in Big Data analysis, and some choices are neither justified nor examined through sensitivity analysis. For instance, the authors chose to winsorize raw returns at the top and bottom 2.5% for each exchange each month. The rationale for choosing winsorizing over trimming, and why the threshold is set at 2.5%, is not explained.

8.3 Conclusions on Results

Our replication of the methodology described by Choi, Gao, and Jiang provides supporting evidence for a correlation between abnormal temperatures and stock returns. We found statistically significant outperformance of a Clean portfolio over an Emission portfolio, consisting of firms in the most polluting industries, during abnormally warm periods in the city of the firm's stock exchange.

Our analysis yielded similar results in terms of significance and direction for portfolios with size-adjusted returns. However, contrary to the original article, we did not find any statistical significance with raw returns, nor in the analysis of global warming's impact on attention using Google Trends data until 2017, while replicating their method. Yet, our regression of Google Trends search volume for the term "global warming" showed a correlation with abnormal temperatures over the extended period 2004-2023. This supports evidence that abnormally warm periods trigger people's attention to global warming exhibited by higher search volume of "global warming" on Google.

Through rolling regressions over 10-year periods, we observed that the correlation between size-adjusted returns of the long-short EMC portfolio and abnormal temperatures diminished over time and became insignificant in the last 5 to 10 years. We speculate, without further evidence, that this could be due to market participants arbitraging away the effect.

Finally, while we found a statistically significant correlation between abnormal temperatures and size-adjusted stock returns of the EMC portfolio, it is important to note that the effect is small (EMC returns decrease by 4 basis points per Fahrenheit degree of abnormal temperature with a t-stat of -3.368) and that correlation does not imply causation.

In Big Data, regression results are sensitive to data pre-processing, and data manipulation is possible. Garbage in, garbage out. So we remain cautious in the interpretation of any correlation found in data, especially with so low R-squared (<0.2%) and explained variance.

9 Appendix

9.1 Industry classification for long-short portfolio EMC

Industry Code (gind)	Industry Name	Emission dummy
101010	Energy Equipment & Services	1
101020	Oil, Gas & Consumable Fuels	1
151010	Chemicals	1
151020	Construction Materials	1
151030	Containers & Packaging	0
151040	Metals & Mining	1
151050	Paper & Forest Products	1
201010	Aerospace & Defense	0
201020	Building Products	0
201030	Construction & Engineering	0
201040	Electrical Equipment	1
201050	Industrial Conglomerates	0
201060	Machinery	1
201070	Trading Companies & Distributors	0
202010	Commercial Services & Supplies	0
202020	Professional Services	0
203010	Air Freight & Logistics	1
203020	Passenger Airlines (New name)	1
203030	Marine Transportation (New Name)	1
203040	Ground Transportation (New Name)	1
203050	Transportation Infrastructure	1
251010	Automobile Components (New Name)	1
251020	Automobiles	1

Industry Code (gind)	Industry Name	Emission dummy
252010	Household Durables	1
252020	Leisure Products	0
252030	Textiles, Apparel & Luxury Goods	0
253010	Hotels, Restaurants & Leisure	0
253020	Diversified Consumer Services	0
255010	Distributors	0
255020	Internet & Direct Marketing Retail (Discontinued)	0
255030	Broadline Retail (New Name)	0
255040	Specialty Retail	0
301010	Consumer Staples Distribution & Retail (New Name)	0
302010	Beverages	1
302020	Food Products	1
302030	Tobacco	1
303010	Household Products	0
303020	Personal Care Products (New Name)	0
351010	Health Care Equipment & Supplies	0
351020	Health Care Providers & Services	0
351030	Health Care Technology	0
352010	Biotechnology	0
352020	Pharmaceuticals	0
352030	Life Sciences Tools & Services	0
401010	Banks	0
401020	Thrifts & Mortgage Finance (Discontinued)	0
402010	Financial Services (New Name)	0
402020	Consumer Finance	0
402030	Capital Markets	0
402040	Mortgage Real Estate Investment Trusts (REITs)	0

Industry Code (gind)	Industry Name	Emission dummy
403010	Insurance	0
451020	IT Services	0
451030	Software	0
452010	Communications Equipment	0
452020	Technology Hardware, Storage & Peripherals	0
452030	Electronic Equipment, Instruments & Components	1
453010	Semiconductors & Semiconductor Equipment	1
501010	Diversified Telecommunication Services	0
501020	Wireless Telecommunication Services	0
502010	Media	0
502020	Entertainment	0
502030	Interactive Media & Services	0
551010	Electric Utilities	1
551020	Gas Utilities	1
551030	Multi-Utilities	1
551040	Water Utilities	0
551050	Independent Power and Renewable Electricity Producers	0
601010	Diversified REITs (New Name)	0
601025	Industrial REITs (New)	0
601030	Hotel & Resort REITs (New)	0
601040	Office REITs (New)	0
601050	Health Care REITs (New)	0
601060	Residential REITs (New)	0
601070	Retail REITs (New)	0
601080	Specialized REITs (New)	0
602010	Real Estate Management & Development (New Code)	0

Industry Code (gind)	Industry Name	Emission dummy

Table 5: Matching table between GIC industries and an emission dummy

9.2 Attention and local temperatures: original paper results

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

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 × Month FEs	Yes	Yes	Yes	Yes
Obs.	11,603	11,603	10,366	10,366
Adj. R^2	.020	.020	.015	.015

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. $*p < .1$; $**p < .05$; $***p < .01$.

9.3 Stock returns and local temperatures: original paper results

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

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

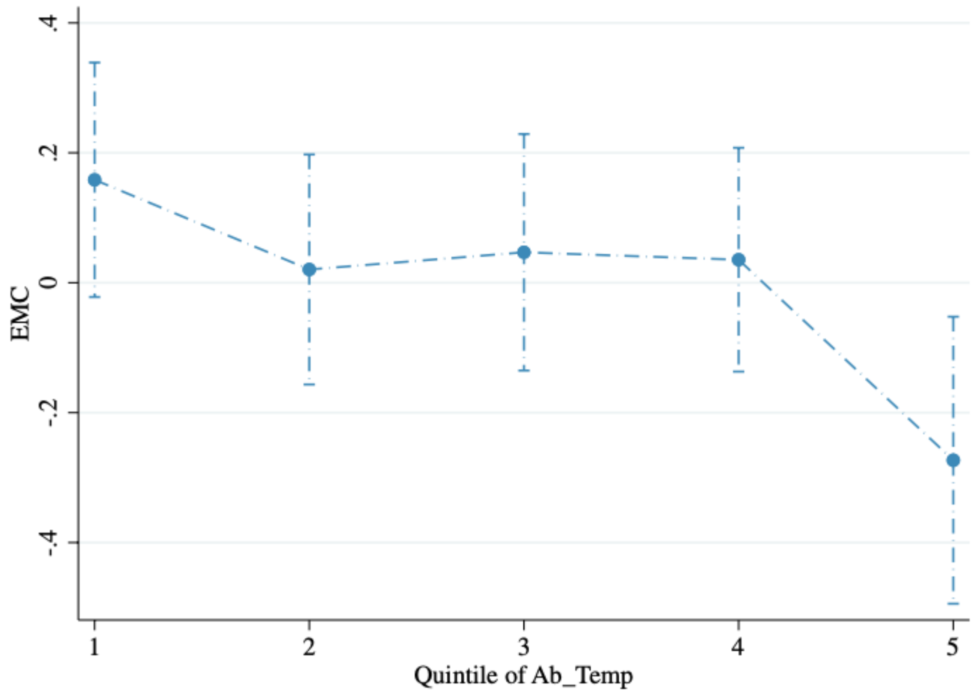


Figure 1
EMC on abnormal temperature, 2001–2017
The figure presents the average EMC returns (equal-weighted and adjusted for year-month fixed effects, as a %) by Ab_Temp quintiles with 95% confidence intervals using the sample for 2001–2017.

References

[1] Darwin Choi, Zhenyu Gao, and Wenxi Jiang. "Attention to Global Warming". In: *The Review of Financial Studies* 33.3 (Feb. 2020), pp. 1112–1145. ISSN: 0893-9454. DOI: 10.1093/rfs/hhz086. eprint: https://academic.oup.com/rfs/article-pdf/33/3/1112/32449232/hhz086.pdf. URL: https://doi.org/10.1093/rfs/hhz086.

[2] Justin Gallagher. "Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States". In: *American Economic Journal: Applied Economics* 6.3 (July 2014), pp. 206–33. DOI: 10.1257/app.6.3.206. URL: https://www.aeaweb.org/articles?id=10.1257/app.6.3.206.

[3] Kalok Chan, Allaudeen Hameed, and Sie Ting Lau. "What If Trading Location Is Different from Business Location? Evidence from the Jardine Group". In: *The Journal of Finance* 58.3 (2003), pp. 1221–1246. ISSN: 00221082, 15406261. URL: http://www.jstor.org/stable/3094578 (visited on 06/14/2024).

[4] Volker Krey et al. "Annex II: Metrics & Methodology". In: *Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.* Ed. by O. Edenhofer et al. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press, 2014.