# Attention to Global Warming*

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**Abstract**

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

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# 1 Introduction

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


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

In this paper, we test how people react to abnormally high local temperatures by examining attention to climate change and stock prices. Our data cover 74 cities in the world with

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

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. Human's collective belief and effort are important determinants of how successful climate policies and campaigns can be. Our study aims to empirically identify how the general public realizes and responds to the impacts of global warming.

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

Our results show that, during abnormally warm months in the city, Google search volume of the topic "Global Warming" increases.[3] Our analysis controls for time fixed effects, and therefore the relationship comes from the geographical variation. Not all cities in 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 temperature, compared to other cities in that month. The effect is the most prominent when the local abnormal temperature is in the city's top quintile, as the weather experience is more salient.

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

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

[3]In this paper, we refer the term "abnormally warm" to cases in which a city's temperature is significantly higher than the historical average temperature at the same point of the year. Our Google data capture the search activity in different cities. See Section 2 for a list of papers that study Google search volume of global warming in the U.S.

outperforms the latter. We sort stocks into high- and low-climate sensitivities using two methods. In the first method, firms are classified as high emission if they belong to industries that IPCC identifies as major emission sources. We also define carbon-intensive and clean firms using their MSCI Carbon Emission Scores, which capture companies' greenhouse gas emissions and are adjusted by industry. Therefore, we are able to study firms that are in carbon-intensive industries as well as high emission firms relative to industry peers. These firms tend to be more sensitive to climate change if climate risk is a systematic factor, if tighter environmental regulations reduce their future cashflows, or if socially responsible investors avoid holding their stocks. Under both classifications, 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. A one standard deviation increase in the city's abnormal temperature is associated with a reduction of 15–37 bps in the long-short emission-minus-clean portfolio. The effect is again more prominent when the abnormal temperature is in the city's top quintile. The return patterns do not seem to be a result of overreaction, as there is no reversal in the longer term. They are observed in both energy and non-energy 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.

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

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

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

## 2 Methodologies and Research Design

We would like to identify investor reaction to global warming in warm local weather. The reaction is first measured by monthly Google Search Volume Index ($SVI$) of the topic "Global Warming" in a city, which proxies for people's attention. Google offers $SVI$ of topics and search terms. Using topics instead of search terms takes care of misspellings and searches in different languages, because 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 look at Google search volume of global warming and climate change and relate it to local weather conditions: e.g., Lineman, Do, Kim, and Joo (2015), Cavanagh et al. (2014), Herrnstadt and Muehlegger (2014), Lang (2014), and Kahn and Kotchen (2011). These studies focus on U.S. data while our paper covers more than 70 cities worldwide and different languages.

To better understand the learning process, we decompose local monthly temperature into 3 components, which account for predictable and seasonal patterns. For example, for the average daily temperature in city $i$ in month $t$, 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 temperature deviation of this month from the average, i.e., the average temperature in city $i$ in the same calendar month over the last 10 years minus $Aver\_Temp_{it}$; and $Ab\_Temp_{it}$ is the remainder.[5] Our focus is how local abnormal temperature, which captures people's new experience, affects attention (as proxied by the change in $SVI$), while controlling for $Aver\_Temp_{it}$ and $Mon\_Temp_{it}$.

Then we turn to investor reaction in the stock market. Specifically, we look at the cross-

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

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

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

We examine monthly size-adjusted stock returns under warm weather. If investors start recognizing the effect of climate on financial markets and buy low-climate-sensitivity and sell high-climate-sensitivity firms, the former will earn higher returns than the latter. We study the short-term as well as the long-term pattern to see if there is any reversal. A reversal may indicate that the short-term price changes overshoot, which implies temporary inefficient allocation of resources in response to global warming.

# 3 Data

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

**Weather**

We obtain daily weather data from the Global Surface Summary of Day Data, produced by the National Climatic Data Center (NCDC). The input data used in building these daily observations are the Integrated Surface Data (ISD), which contain weather records from over 9,000 stations globally. The weather conditions include temperature, wind, cloudiness, precipitation, snow depth, and others. The data are available since 1973. For our analysis, we collect the daily temperature data for 74 cities with major stock exchanges. By identifying the location coordinates, we select the closest weather station to the address of the exchange.

**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" since 2004. We download the monthly $SVI$ in each of the 74 locations from 2004 to 2016. All searches are at the city level, except for some small countries where the search volume data are only available at the country level.[6]

**Stock and company information**

Monthly stock returns, market capitalization, and industry information are available from Thomson Reuters DataStream. DataStream covers more than 100,000 equities in nearly 200 countries from 1980 onwards. The literature points out that DataStream may suffer from 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 non-local firms (i.e., firms whose $GEOG$ code is different from the country in which the market is located), monthly returns that are above 300% and reversed within one month, and zero returns (DataStream repeats the last valid data point for delisted firms).

**Carbon emission**

As explained in Section 4.2, we identify high emission firms in two ways. First, Intergovernmental Panel on Climate Change (IPCC) defines industries that are major emission sources (Krey et al., 2014). All firms in these industries are classified as high emission firms. Second, we get firms' carbon emission estimates from MSCI ESG Ratings, which analyze

[6]We also download the monthly $SVI$ of the topic "Climate Change," but the search traffic of this topic is much lower than that of "Global Warming" in the first few years of our sample period. In more recent years, $SVI$ of the two topics is highly correlated. In the paper we report the results using $SVI$ of "Global Warming."

companies' environmental, social, and governance issues since 2007. Specifically, MSCI ESG studies greenhouse gas (GHG) emissions of more than 8,600 companies worldwide. They collect 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, they use GHG data reported by the Carbon Disclosure Project or government databases. The Carbon Emission Score on a scale of 0–10 is given to each firm in each year.[7] Companies with better performance on this issue score higher. The score is adjusted by industry, and thus is comparable for two firms from different industries.

# 4 Empirical Results

Given that climate change is a global phenomenon, it is critical to conduct our study in a broad international setting, in order to understand people's collective beliefs and reactions to the issue. Our tests aim to investigate two questions: (1) whether people's attention varies with local temperatures, and (2) if any, how the attention induced by local temperatures affects the stock price of local firms. The international setting also gives us an additional identification advantage: climate science research shows that extreme temperatures rarely occur simultaneously in both Northern and Southern Hemispheres (see, e.g., Neukom et al., 2014). Table I shows the list of 74 stock exchange cities and the number of unique stocks in each city in our sample. In all regressions below, all standard errors are clustered by exchange city and year-month.

## 4.1 Attention and local temperatures

To capture changes in attention, we first calculate the log monthly change of Google Search Volume Index, $DSVI$. $DSVI_{it}$ is the log change of $SVI$ in city $i$ in month $t$, adjusted

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

for seasonality.[8] Panel A of Table II 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 Eq.(1). The mean $DSVI$ is close to zero (0.01%), while the mean $Aver\_Temp$, $Mon\_Temp$, and $Ab\_Temp$ are 61.9°F, 0.16°F, and 0.26°F, respectively.

Then we run the following regression:

$$DSVI_{it} = \alpha + \beta_1 Aver\_Temp_{it} + \beta_2 Mon\_Temp_{it} + \beta_3 Ab\_Temp_{it} + \epsilon_{it}, \tag{2}$$

Our coefficient of interest is $\beta_3$. Results are reported in Table II, Panel B. In Column (1), the coefficient estimate of $Ab\_Temp$ is significantly positive ($t$-stat = 2.3). This suggests that people pay more attention to global warming when they are experiencing 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 more about global warming than people in other places). As a side note, neither $Aver\_Temp$ nor $Mon\_Temp$, the predictable parts of temperature based on past data, is statistically significant. People's attention therefore reacts more to new experience that is different from previous patterns. In Column (2) and all the remaining tests, we drop $Aver\_Temp$ and $Mon\_Temp$ and focus on $Ab\_Temp$.

In Column (3), 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 quintile dummies indicate that the temperature effect is non-linear: 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

[8] $DSVI$ is defined as the residuals from the regression of log change of monthly $SVI$ on month-of-the-year dummies. The residuals are then winsorized at the top and bottom 2.5% tails. Two cities, Shenzhen and Shanghai, are dropped from the analysis because there are no valid local Google search data.

that investors pay more attention to infrequent dramatic changes than to frequent gradual changes.

It is worth noting the economic magnitude. Based on the estimation in Column (3), 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%, shown in Panel A).

## 4.2 Definitions of high emission firms

We next examine whether extra attention affects stock prices, focusing on the differential reactions in the cross-section of firms. As discussed in Section 2, we expect that updated beliefs about global warming will make stocks of high emission firms underperform stocks of low emission firms. Two methods are used to identify high emission firms. First, we adopt the industry definitions provided by Inter-governmental 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 chemical and metal, etc.); and Agriculture, Forestry, and Other Land Use (AFOLU). Within each sector there are subcategories (a full list can be found in Krey et al., 2014). 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 rely on the firm-level MSCI carbon emission scores in each year. A high score corresponds to low emission relative to industry peers in that year. We define high- (low-) carbon emission firms as firms whose MSCI carbon emission scores at the previous year-end are in the lowest (highest) tercile in the exchange city. Using IPCC definitions and MSCI scores allows us to compare high emission and low emission at both the industry and firm levels. For example, Toyota Motor Corporation, listed on Tokyo Stock Exchange, belongs to

[9] For example, Coal (DataStream Industry Group = 49), Gold Mining (DataStream Industry Group = 119), and General Mining (DataStream Industry Group = 122) are matched with Mining and Quarrying (IPCC Code = 1A2f4).

the Automobiles industry (which is mapped to Transport Equipment industry, IPCC Code = 1A2f2). It is classified as a high emission firm according to the first method. 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 the years. One can interpret that the company is a relatively clean firm in a high emission industry.

## 4.3 Pricing effect of temperature-induced attention

We first form two portfolios according to the IPCC definitions. In each city $i$ during 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 put into portfolio $CLEAN_i$. A long-short portfolio $EMC_i$ (which stands for Emission Minus Clean) is formed by buying $EMISSION_i$ and selling $CLEAN_i$ short. We construct all portfolios using equal weights and value weights. Panel A of Table III shows the summary statistics. Size-adjusted returns, defined as the stock's return in month $t$ minus the average return of stocks in the same size quintile in the exchange, are reported.[10] 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 significant underperformance in the warmest quintile, a result that will be further confirmed in the regression analysis below. Summary statistics for raw returns (not adjusted for size) and longer-term returns (up to 6 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 the morning sunshine in the city and the index returns, we capture investors' experience by using the local abnormal temperature in the city. We run the

[10] We use size-adjusted returns as the market capitalization data obtained from DataStream have better coverage than other financial data. There are other models for calculating adjusted returns (e.g., a factor model that is based on momentum and cashflow-to-price, Hou, Karolyi, and Kho, 2011). One disadvantage is that the sample size would be greatly reduced when requiring other company information.

following regression:

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

where $EMC_{it}$ is the value-weighted or equal-weighted, size-adjusted or raw return of $EMC$ portfolio in city $i$ in month $t$ (during 2001 to 2017), and $Ab\_Temp_{it}$ is the abnormal temperature in the city $i$ in month $t$ based on the decomposition in Eq.(1). Year-month fixed effects are included. Results are in Panel B (equal-weighted) and Panel C (value-weighted). Column (1) of Panel B shows that higher abnormal temperature is associated with significantly lower $EMC$ size-adjusted returns. A one standard deviation increase in $Ab\_Temp$ corresponds to a decrease of 16bps in $EMC$ return ($= -0.058 \times 2.676$). Column (2) replaces $Ab\_Temp$ with the qunitile 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. There is a sizable economic impact, with a change from temperature quintile 1 (coolest) to quintile 5 (warmest) corresponding to a drop of 48bps ($t$-stat $= -4.0$) in size-adjusted return. The results are similar when we look at value-weighted returns (Columns (1) and (2) of Panel C) and raw returns (Columns (3) and (4) of Panels B and C). 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) in the warmest quintile, at 1% significance level. Therefore, both portfolios contribute to the low $EMC$ returns in the warmest months.

The return patterns in month $t$ are consistent with the reactions in attention measures documented in Section 4.1. Extra attention paid to global warming when the local temperature is abnormally high, particularly in the warmest months, is associated with lower contemporaneous returns for firms in high emission industries.

We next examine the long-term performance subsequent to an abnormally warm month (for brevity, only equal-weighted $EMC$ size-adjusted returns are reported):

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

where $n = \{3, 6\}$ and the returns are measured from month $t+1$ to month $t+n$. Year-month fixed effects are included. If $\beta_1$ is negative or zero, it is more consistent with the belief updating story; investors with limited attention generally overlooks climate risk, but recognizes it when reacting to attention-grabbing weather events. Otherwise if $\beta_1$ appears to be positive, it implies overreaction as the previous price pattern at $t$ has reversed. Table IV presents the result.

As shown in Columns (1) and (3), the coefficients of $Ab\_Temp$ are statistically insignificant. The coefficients of temperature quintiles in Columns (2) and (4) do not show a systematic pattern and are generally statistically insignificant. These results indicate that there is no strong continuation or reversal in the three to six months after month $t$. However, all coefficient estimates are negative, which may suggest that some continuation is not detected in the return data, and it calls for an analysis using investors' trading behavior. In future tests, we will study trading activity of high emission firms using international institutional investors' holdings, available from Factset. Table V reruns the portfolio return regressions in Panel B of Table III with 33 exchange cities where Factset data are available. The results are similar to the full sample of 74 exchange cities.

One concern about the IPCC industry classification is that we may pick up some industry effects. Although it is unlikely that such effects vary with local abnormal temperature, we conduct three additional tests to further confirm our previous results. First, we rerun the return regressions in Eq.(3) using an earlier sample period, 1983 (the beginning year of our abnormal temperature measures) to 2000. Unlike Panel B of Table III (whose sample period is 2001–2017), Table VI does not show any systematic difference in $EMISSION$ and $CLEAN$ portfolio returns under different abnormal temperatures. Global warming was less of a public concern and scientific evidence was inconclusive before the 21$^{\text{st}}$ century.[11] It is not surprising that we only observe the return pattern after 2001 if this is due to the

[11] For example, in its Third Assessment Report released in 2001, 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." A joint statement was issued in 2001 by national science academies of many different countries, stating that "IPCC represents the consensus of the international scientific community on climate change science."

awareness of global warming.

Second, some high emission industries' returns may be correlated with fluctuations in oil prices. In Table VII, we 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, and the effects are similar. Non-energy industries do not show weaker results, confirming that investors more likely react to different carbon emission levels than to oil prices. Our last test defines high emission firms by their MSCI carbon emission scores. As these scores are industry-adjusted, it is now possible to have both high and low emission firms in the same industry, and therefore this test will not be driven by industry effects. Note that this analysis is done with a smaller sample (with 14 exchanges), as MSCI scores are only available since 2007 and cover only a subset of exchanges and firms. In each city $i$ in month $t$, $EMISSION_{it}$ is an equal-weighted portfolio of firms whose MSCI scores in the previous calendar year are in the bottom tercile in the city; $CLEAN_{it}$ is an equal-weighted portfolio of firms in the top decile; and $EMC_{it}$ is the long-short portfolio. Results in Table VIII show similar pattern. $EMC$ earns lower return when the city's $Ab\_Temp$ is high, especially when it is in the highest quintile. In Column (1), a one standard deviation increase in $Ab\_Temp$ corresponds to a decrease of 37bps in $EMC$ size-adjusted return ($t$-stat $= -2.5$).

# 5 Conclusion

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

We show that people revise their beliefs upwards when the local temperature is unusually warm. There is higher Google search activity on the topic "Global Warming." In financial markets, carbon-intensive firms underperform in the month when the exchange city is abnormally warm, and there is no sign of reversal in the longer term. These findings are consistent with limited attention, under which people focus on attention-grabbing weather events and personal experiences. While climate change is a long-term trend, local weather is more visible even though it may not be relevant for the global trend.

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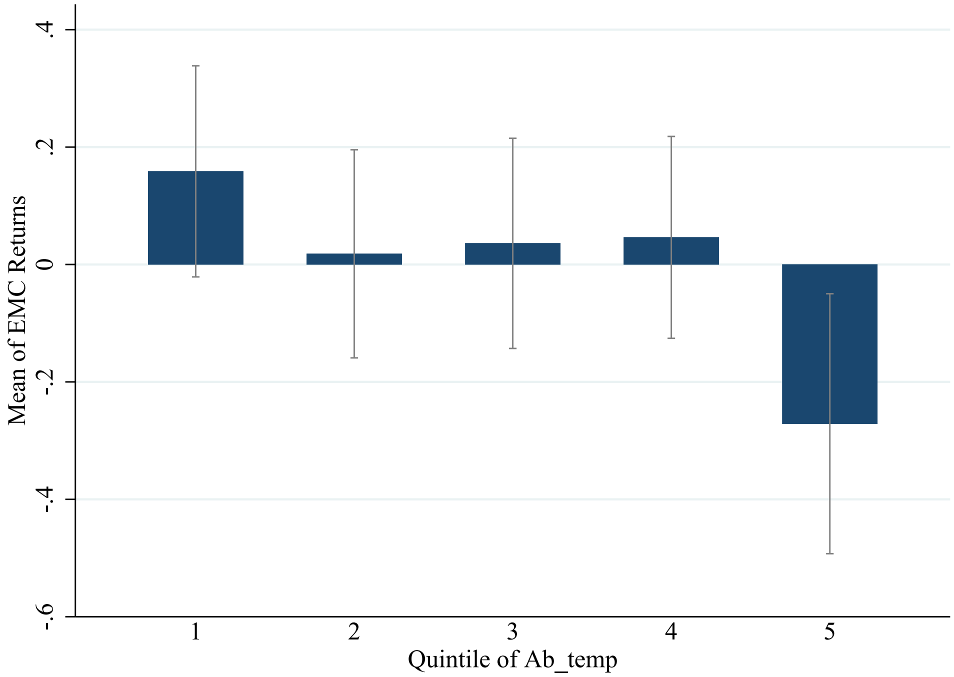
**Figure I.** EMC on Abnormal Temperature: 2001-2017




The figure presents the average of EMC returns (EW) by Ab_Temp quintiles with 95% confidence intervals using the sample of 2001–2017.

**Table I.** List of exchange cities

This table lists the 74 exchange cities that we use in analyses and the number of unique stocks during the sample period of 2001 to 2017.

| Exchange City | Country/Region | Continent | # of Unique Stockes |
|---|---|---|---|
| Amman | Jordan | Asia | 239 |
| Amsterdam | Netherlands | Europe | 295 |
| Athens | Greece | Europe | 393 |
| Bangkok | Thailand | Asia | 811 |
| Berlin | Germany | Europe | 120 |
| Bern | Switzerland | Europe | 19 |
| Bogota | Columbia | South America | 82 |
| Bratislava | Slovakia | Europe | 69 |
| Brussels | Belgium | Europe | 289 |
| Bucharest | Romania | Europe | 280 |
| Budapest | Hungary | Europe | 83 |
| Buenos Aires | Argentina | South America | 103 |
| Bulgarian | Bulgaria | Europe | 264 |
| Busan | Korea | Asia | 1027 |
| Cairo | Egypt | Africa | 254 |
| Colombo | Sri Lanka | Asia | 301 |
| Copenhagen | Denmark | Europe | 309 |
| Cyprus | Cyprus | Europe | 186 |
| Dhaka | Bangladesh | Asia | 427 |
| Dublin | Ireland | Europe | 76 |
| Dusseldorf | Germany | Europe | 69 |
| Frankfurt | Germany | Europe | 1878 |
| Hamburg | Germany | Europe | 76 |
| Hanoi | Vietnam | Asia | 421 |
| Harare | Zimbabwe | Africa | 71 |
| Helsinki | Finland | Europe | 213 |
| Ho Chi Minh | Vietnam | Asia | 357 |
| Hong Kong | Hong Kong | Asia | 2093 |
| Istanbul | Turkey | Europe | 476 |
| Jakarta | Indonesia | Asia | 601 |
| Johannesburg | South Africa | Africa | 701 |
| Karachi | Pakistan | Asia | 477 |
| Kiev | Ukraine | Europe | 102 |
| Kuala Lumpur | Malaysia | Asia | 1210 |
| Kuwait | Kuwait | Asia | 180 |
| Lagos | Nigeria | Africa | 185 |
| Lima | Peru | South America | 162 |
| Lisbon | Portugal | Europe | 104 |

| | | | |
|---|---|---|---|
| Ljubljana | Slovenia | Europe | 193 |
| London | U.K. | Europe | 3996 |
| Luxembourg | Luxembourg | Europe | 47 |
| Madrid | Spain | Europe | 320 |
| Manila | Philippines | Asia | 284 |
| Mexico City | Mexico | North America | 188 |
| Milan | Italy | Europe | 527 |
| Moscow | Russia | Europe | 498 |
| Mumbai | India | Asia | 4946 |
| Munich | Germany | Europe | 98 |
| Muscat | Oman | Asia | 125 |
| Nagoya | Japan | Asia | 118 |
| New York | U.S. | North America | 3904 |
| Osaka | Japan | Asia | 145 |
| Oslo | Norway | Europe | 453 |
| Paris | France | Europe | 1627 |
| Prague | Czechia | Europe | 119 |
| Riyadh | Saudi Arabia | Asia | 185 |
| Santiago | Chile | South America | 250 |
| Sao Paulo | Brazil | South America | 354 |
| Shanghai | China | Asia | 1181 |
| Shenzhen | China | Asia | 2024 |
| Singapore | Singapore | Asia | 945 |
| Skopje | Macedonia | Europe | 54 |
| Stockholm | Sweden | Europe | 1131 |
| Stuttgart | Germany | Europe | 140 |
| Sydney | Australia | Oceania | 2980 |
| Taipei | Taiwan | Asia | 1027 |
| Tel Aviv | Israel | Asia | 822 |
| Tokyo | Japan | Asia | 3843 |
| Toronto | Canada | North America | 891 |
| Vienna | Austria | Europe | 172 |
| Warsaw | Poland | Europe | 1092 |
| Wellington | New Zealand | Oceania | 243 |
| Zagreb | Croatia | Europe | 121 |
| Zurich | Switzerland | Europe | 409 |

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

This table reports the result of analyses on the effect of abnormal temperature on Google search volume of "global warming". Panel A presents summary statistics of variables. $DSVI$ is monthly log change of Google's search volume index (SVI) of the topic "global warming" and adjusted for seasonality. *Average_ Temp* is the average monthly temperature (in Fahrenheit degrees) of the exchange's city over the past 120 months. *Monthly_ Temp* is the city's average temperature in the same month of the year over the past 10 years minus *Average_ Temp*. *Ab_ Temp* is the city's temperature in this month minus *Average_ Temp* and *Monthly_ Temp*. Panel B represents the result of regressing $DSVI$ on temperature measures. For each exchange city, months are sorted into quintiles based on *Ab_ Temp*, and *Ab_ Temp Quintile 2-5* are quintile dummies which equal one if the month belongs to quintile 2-5, respectively. The sample is from 2004 to 2017. Standard errors are clustered by exchange city and by year–month, and the corresponding $t$-statistics are reported in parentheses.

Panel A: Summary statistics

| | Mean | S.D. | P10 | P25 | P50 | P75 | P90 | N |
|---|---|---|---|---|---|---|---|---|
| DSVI(%) | 0.012 | 66.469 | -51.411 | -23.212 | -0.604 | 22.706 | 51.584 | 11593 |
| Aver_Temp | 61.862 | 12.453 | 48.337 | 51.657 | 59.459 | 72.403 | 81.695 | 11593 |
| Mon_Temp | 0.159 | 10.836 | -15.176 | -8.062 | 0.259 | 8.178 | 15.510 | 11593 |
| Ab_Temp | 0.264 | 2.673 | -2.792 | -1.201 | 0.238 | 1.694 | 3.418 | 11593 |
| # of unique exchanges | 72 | | | | | | | |

Panel B: Regression of $DSVI$ on abnormal temperature

| Dep. Var.: DSVI (%) | (1) | (2) | (3) |
|---|---|---|---|
| Aver_Temp | -0.004 | | |
| | (-0.43) | | |
| Mon_Temp | -0.006 | | |
| | (-0.11) | | |
| Ab_Temp | 0.531 | 0.532 | |
| | (2.26) | (2.26) | |
| Ab_temp Quintile 2 | | | 0.720 |
| | | | (0.38) |
| Ab_temp Quintile 3 | | | 1.252 |
| | | | (0.87) |
| Ab_temp Quintile 4 | | | 1.056 |
| | | | (0.57) |
| Ab_temp Quintile 5 | | | 4.842 |
| | | | (2.58) |
| Year*Month FE | Yes | Yes | Yes |
| N | 11593 | 11593 | 11593 |
| R-sq | 0.034 | 0.034 | 0.034 |

**Table III.** 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 IPCC's report. Portfolio return (in percent) equals the average adjusted return of stocks at month $t$, equal weighted (EW) or value weighted (VW). Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. $EMC$ equals $EMISSION$ minus $CLEAN$. $EMC\_Raw$ is calculated using raw returns. $EMC_{t+1,t+3}$ and $EMC_{t+1,t+6}$ are calculated using adjusted returns over months $t+1$ to $t+3$ and $t+1$ to $t+6$, respectively. Panel A reports summary statistics. Panel B reports the result of regressions of $EMC$ on contemporaneous temperature variables using equal-weighted portfolio returns, while Panel C uses value-weighted returns. The sample is from 2001/01 to 2017/12. Standard errors are clustered by exchange city and year–month, and the corresponding $t$-statistics are reported in parentheses.

Panel A: Summary statistics

| | Mean | S.D. | P10 | P25 | P50 | P75 | P90 | N |
|---|---|---|---|---|---|---|---|---|
| EMC(EW)$_t$ | 0.048 | 4.851 | -3.525 | -1.462 | 0.000 | 1.656 | 3.809 | 12615 |
| EMC_Raw(EW)$_t$ | 0.059 | 5.729 | -4.163 | -1.692 | 0.107 | 1.914 | 4.521 | 12615 |
| EMISSION(EW)$_t$ | 0.028 | 3.278 | -2.079 | -0.838 | 0.000 | 0.970 | 2.283 | 12615 |
| CLEAN(EW)$_t$ | -0.020 | 1.982 | -1.370 | -0.591 | 0.000 | 0.528 | 1.349 | 12615 |
| EMC(VW)$_t$ | 0.104 | 5.972 | -5.137 | -2.204 | 0.059 | 2.517 | 5.584 | 12615 |
| EMC_Raw(VW)$_t$ | 0.118 | 6.699 | -5.618 | -2.410 | 0.125 | 2.726 | 6.077 | 12615 |
| EMISSION(VW)$_t$ | 0.037 | 4.276 | -3.554 | -1.545 | 0.002 | 1.697 | 3.795 | 12615 |
| CLEAN(VW)$_t$ | -0.067 | 3.089 | -2.931 | -1.345 | -0.026 | 1.180 | 2.796 | 12615 |
| EMC(EW)$_{t+1,t+3}$ | 0.061 | 6.605 | -5.594 | -2.246 | 0.142 | 2.665 | 5.824 | 12615 |
| EMC(EW)$_{t+1,t+6}$ | 0.126 | 9.126 | -8.308 | -3.325 | 0.278 | 4.122 | 8.418 | 12615 |
| Ab_Temp | 0.307 | 2.676 | -2.776 | -1.142 | 0.306 | 1.746 | 3.446 | 12615 |
| # of unique exchanges | 74 | | | | | | | |

Panel B: Equal-weighted EMC returns

| EW(%) | EMC | | EMC_Raw | | EMISSION | CLEAN |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ab_Temp | -0.058 | | -0.067 | | | |
| | (-3.18) | | (-2.65) | | | |
| Ab_Temp Quintile 2 | | -0.150 | | -0.286 | -0.039 | 0.112 |
| | | (-1.19) | | (-1.65) | (-0.48) | (1.90) |
| Ab_Temp Quintile 3 | | -0.136 | | -0.302 | -0.043 | 0.093 |
| | | (-0.96) | | (-1.54) | (-0.43) | (1.67) |
| Ab_Temp Quintile 4 | | -0.134 | | -0.203 | -0.085 | 0.049 |
| | | (-1.18) | | (-1.59) | (-1.39) | (0.85) |
| Ab_Temp Quintile 5 | | -0.479 | | -0.597 | -0.283 | 0.195 |
| | | (-4.01) | | (-3.72) | (-3.29) | (3.97) |
| Year*Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 12615 | 12615 | 12615 | 12615 | 12615 | 12615 |
| $R^2$ | 0.036 | 0.036 | 0.034 | 0.034 | 0.030 | 0.039 |

Panel C: Value-weighted EMC returns

| VW(%) | EMC | | EMC_Raw | | EMISSION | CLEAN |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ab_Temp | -0.055 | | -0.065 | | | |
| | (-2.08) | | (-2.00) | | | |
| Ab_Temp Quintile 2 | | -0.213 | | -0.313 | -0.078 | 0.135 |
| | | (-1.14) | | (-1.35) | (-0.72) | (1.27) |
| Ab_Temp Quintile 3 | | -0.347 | | -0.512 | -0.208 | 0.138 |
| | | (-1.87) | | (-2.19) | (-1.84) | (1.39) |
| Ab_Temp Quintile 4 | | -0.306 | | -0.434 | -0.169 | 0.137 |
| | | (-1.77) | | (-2.39) | (-1.64) | (1.55) |
| Ab_Temp Quintile 5 | | -0.477 | | -0.572 | -0.323 | 0.155 |
| | | (-3.10) | | (-2.81) | (-3.12) | (1.65) |
| Year*Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 12615 | 12615 | 12615 | 12615 | 12615 | 12615 |
| $R^2$ | 0.051 | 0.051 | 0.049 | 0.049 | 0.043 | 0.047 |

**Table IV.** Long-term EMC returns subsequent to abnormal temperature

The table report the result of regressions of $EMC_{t+1,t+3}$ or $EMC_{t+1,t+6}$ on abnormal temperature variables at month $t$. EMC are calculated using equal-weighted average of adjusted returns. The sample is from 2001 to 2017. Standard errors are clustered by exchange city and year–month, and the corresponding $t$-statistics are reported in parentheses.

| EMC (%) | $t+1$ to $t+3$ | | $t+1$ to $t+6$ | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Ab_Temp | -0.049 | | -0.014 | |
| | (-1.43) | | (-0.47) | |
| Ab_Temp Quintile 2 | | -0.281 | | -0.067 |
| | | (-1.26) | | (-0.24) |
| Ab_Temp Quintile 3 | | -0.192 | | -0.049 |
| | | (-1.45) | | (-0.21) |
| Ab_Temp Quintile 4 | | -0.430 | | -0.117 |
| | | (-2.67) | | (-0.46) |
| Ab_Temp Quintile 5 | | -0.365 | | -0.092 |
| | | (-1.55) | | (-0.39) |
| Year*Month FE | Yes | Yes | Yes | Yes |
| N | 12615 | 12615 | 12615 | 12615 |
| $R^2$ | 0.049 | 0.049 | 0.063 | 0.063 |

**Table V.** EMC return and abnormal temperature: robustness test using the FactSet sample

At the beginning of month $t$, $EMISSION$ and $CLEAN$ portfolios are formed based on firms' industry code. High carbon emission industries are defined following IPCC's report. Portfolio return (in percent) 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 $CLEAN$. $EMC\_Raw$ is calculated using raw returns. This tables reports the result of regressions of $EMC$ on contemporaneous temperature variables. The sample is from 2001/01 to 2017/12 and only includes stock exchanges that are in FactSet dataset. Standard errors are clustered by exchange city and year–month, and the corresponding $t$-statistics are reported in parentheses.

| EW(%) | EMC | | EMC_Raw | | EMISSION | CLEAN |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ab_Temp | -0.056 | | -0.051 | | | |
| | (-2.16) | | (-1.89) | | | |
| Ab_Temp Quintile 2 | | -0.073 | | 0.015 | 0.006 | 0.079 |
| | | (-0.72) | | (0.10) | (0.09) | (1.80) |
| Ab_Temp Quintile 3 | | -0.005 | | -0.070 | 0.115 | 0.119 |
| | | (-0.02) | | (-0.22) | (0.64) | (1.39) |
| Ab_Temp Quintile 4 | | -0.135 | | -0.021 | -0.057 | 0.078 |
| | | (-0.95) | | (-0.14) | (-0.68) | (1.22) |
| Ab_Temp Quintile 5 | | -0.547 | | -0.466 | -0.363 | 0.185 |
| | | (-2.43) | | (-2.50) | (-2.15) | (2.47) |
| Year*Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 5992 | 5992 | 5992 | 5992 | 5992 | 5992 |
| $R^2$ | 0.069 | 0.070 | 0.070 | 0.070 | 0.061 | 0.078 |
| # of unique exchanges | 33 | | | | | |

**Table VI.** EMC return and abnormal temperature: placebo test using 1983–2000

At the beginning of month $t$, $EMISSION$ and $CLEAN$ portfolios are formed based on firms' industry code. High carbon emission industries are defined following IPCC's report. Portfolio return (in percent) 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 $CLEAN$. $EMC\_Raw$ is calculated using raw returns. This tables reports the result of regressions of $EMC$ on contemporaneous temperature variables using equal-weighted portfolio returns. The sample is from 1983/01 to 2000/12. Standard errors are clustered by exchange city and year–month, and the corresponding $t$-statistics are reported in parentheses.

| EW(%) | EMC | | EMC_Raw | | EMISSION | CLEAN |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ab_Temp | -0.001 | | 0.047 | | | |
| | (-0.05) | | (1.40) | | | |
| Ab_Temp Quintile 2 | | 0.099 | | 0.418 | 0.053 | -0.046 |
| | | (0.45) | | (1.86) | (0.48) | (-0.38) |
| Ab_Temp Quintile 3 | | 0.116 | | 0.261 | 0.054 | -0.062 |
| | | (0.46) | | (0.97) | (0.39) | (-0.48) |
| Ab_Temp Quintile 4 | | 0.093 | | 0.477 | 0.044 | -0.049 |
| | | (0.51) | | (1.99) | (0.39) | (-0.63) |
| Ab_Temp Quintile 5 | | -0.042 | | 0.362 | -0.002 | 0.040 |
| | | (-0.21) | | (1.30) | (-0.02) | (0.38) |
| Year*Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 8998 | 8998 | 8998 | 8998 | 8998 | 8998 |
| $R^2$ | 0.039 | 0.039 | 0.038 | 0.038 | 0.041 | 0.033 |
| # of unique exchanges | 63 | | | | | |

**Table VII.** EMC return and abnormal temperature: energy vs non-energy firms

High carbon emission firms are divided into energy and non-energy firms and form the EMC portfolio separately. Portfolio return (in percent) is the equal-weighted (EW) average adjusted return. Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. $EMC$ equals $EMISSION$ minus $CLEAN$. This tables reports the result of regressions of $EMC$ on contemporaneous temperature variables. The sample is from 2001/01 to 2017/12. Standard errors are clustered by exchange city and year–month, and the corresponding $t$-statistics are reported in parentheses.

| EMC(EW, %) | Energy | | Non-energy | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Ab_Temp | -0.083 | | -0.046 | |
| | (-2.54) | | (-2.16) | |
| Ab_Temp Quintile 2 | | -0.137 | | -0.170 |
| | | (-0.60) | | (-1.28) |
| Ab_Temp Quintile 3 | | -0.291 | | -0.088 |
| | | (-1.33) | | (-0.59) |
| Ab_Temp Quintile 4 | | -0.187 | | -0.105 |
| | | (-1.00) | | (-0.85) |
| Ab_Temp Quintile 5 | | -0.405 | | -0.488 |
| | | (-1.90) | | (-3.59) |
| Year*Month FE | Yes | Yes | Yes | Yes |
| N | 10744 | 10744 | 12538 | 12538 |
| $R^2$ | 0.059 | 0.059 | 0.031 | 0.031 |
| # of unique exchanges | 70 | | 74 | |

**Table VIII.** EMC return and abnormal temperature: using MSCI ratings

Stocks are sorted into high- and low-carbon emission portfolios based on the most recent year-end MSCI carbon emission scores. The high-carbon emission portfolio, labeled as $EMISSION$ includes stocks with carbon emission score lower than 3. The low-carbon emission portfolio, labeled as $CLEAN$ includes stocks with carbon emission score higher than 7. Portfolio return (in percent) is calculated as the equal weighted (EW) average adjusted return of stocks. Adjusted return equals raw return minus the average return of stocks in the same size quintile by each exchange. $EMC$ equals $EMISSION$ minus $CLEAN$. The table reports the result of regressions of $EMC$ on contemporaneous temperature variables. The sample is from 2008/01 to 2017/12 and only includes exchanges with more than 30 stocks covered by MSCI. Standard errors are clustered by exchange city and year–month, and the corresponding $t$-statistics are reported in parentheses.

| EW(%) | EMC | | EMC_Raw | | EMISSION | CLEAN |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Ab_Temp | -0.139 | | -0.140 | | | |
| | (-2.48) | | (-2.32) | | | |
| Ab_Temp Quintile 2 | | -0.290 | | -0.311 | -0.036 | 0.255 |
| | | (-0.47) | | (-0.50) | (-0.10) | (0.65) |
| Ab_Temp Quintile 3 | | -0.774 | | -0.833 | -0.439 | 0.335 |
| | | (-1.68) | | (-1.71) | (-1.65) | (0.70) |
| Ab_Temp Quintile 4 | | -0.105 | | -0.062 | -0.042 | 0.063 |
| | | (-0.25) | | (-0.14) | (-0.11) | (0.18) |
| Ab_Temp Quintile 5 | | -0.860 | | -0.891 | -0.273 | 0.587 |
| | | (-1.79) | | (-1.68) | (-0.77) | (1.54) |
| Year*Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 795 | 795 | 795 | 795 | 795 | 795 |
| $R^2$ | 0.369 | 0.369 | 0.379 | 0.380 | 0.409 | 0.237 |
| # of unique exchanges | 14 | | | | | |