Warming Trends: Analysing the Impact of Temperature anomaly on the risk and return of the US stock market.

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Abstract

In this study, I examine how temperature anomalies affect the stock returns and volatility of US public companies, particularly those in heat-sensitive industries. This study employs a panel data fixed effect regression to analyze climate data alongside financial data from around 18000 firms located and traded in the US continental in order to examine the relationship between temperature anomalies and US stock market dynamics. To determine whether this can be attributed to the effect of temperature on firms' infrastructure or to the sentimental effect of temperature on investors' sentiments. I found no evidence that temperature affects US firms' stocks return. However, I find some evidence to suggest that it may affect US stocks' standard deviation.

Keywords: Temperature anomaly, US, Climate risk, Investor sentiments, Heat-sensitive industries

1 Introduction

According to the IPCC's Sixth Assessment Report, climate change causes widespread and permanent impacts on ecosystems and human communities at current levels. Climate change at 1.5 degrees Celsius will cause more severe climate risks, including extreme weather events and rising sea levels. This will have significant consequences for the natural and human systems. It emphasizes the need for immediate and sustained prevention measures to limit warming to this threshold. It also highlights the need for robust adaptation measures to deal with unavoidable impacts. As a result, there is an urgent need for a comprehensive global response to mitigate risks and protect future generations. In Lau and Nath [2012], they analyze the heat waves occurring in North America and identify regions, such as the Great Plains and the West Coast, where significant changes in temperature occur. The severity, duration, frequency, and geographical extent of heat waves are expected to increase in the 21st century in comparison to the 20th century.

However, despite numerous pieces of evidence that demonstrate that climate change is occurring, the issue has always been a matter of debate among people, especially among Republicans and Democrats in the US, concerning whether climate change negatively impacts different parts of the US economy or whether the resulting laws such as those related to carbon emissions negatively affect the economy. As a result of US withdrawal from the Paris climate agreement by Donald Trump due to alleged downsides associated with potential loss for US companies, this conflict has increased. The study by McCright and Dunlap [2011] shows that for liberals and Democrats, higher education increases alignment with scientific consensus and concern, but for conservatives and Republicans, these factors have a weaker or even negative impact. According to Ongena and Özlem Dursun-de Neef [2024], people who experience higher temperatures tend to change their beliefs and withdraw money from banks with more fossil fuel financing, and this change is more evident in regions where republicans are more popular as climate change deniers. Therefore, climate change, especially in the US, is a subjective matter, and research findings in this field are essential for investors and policymakers to gain a better understanding of beliefs and reactions regarding global warming.

A variety of literature can be used to gain a better understanding of the effect of the high temperature on economic parameters. According to Dell et al. [2012], changes in temperature have a significant impact on economic growth. Their research indicates that high temperatures negatively affect the economic growth of poorer countries. They highlight the fact that even a 1°C increase in temperature can have a significant impact on economic growth. In contrast, wealthier nations, such as the US, are better able to resist these effects. There is a possibility that wealthier countries are able to cope with and adapt to changes in temperature due to a more robust and resistant system. Jones and Olken [2010], however, highlight that increasing temperatures may also negatively affect the welfare of rich countries via imports from poor countries. Makridis and Schloetzer [2022] found that extreme temperatures (below 15 and above 85 degrees Fahrenheit) affect people's beliefs about current and future economic growth in the US. These economic sentiments are more prevalent among highly skilled individuals who have higher cognitive demands at work.

According to Pankratz et al. [2023], companies in developing countries experience lower profits when the temperature is high and fluctuates, and their economy has not fully accounted for the impact of heat on corporate profitability. Addoum et al. [2020] examined how temperature affects firms and establishment sales and productivity in US companies both at the firm and establishment levels. According to their results, there is a small, insignificant correlation between the variables. But, further research by Addoum et al. [2023] indicates that temperature shocks affect earnings in 40 percent of industries and are not limited to agriculture. This illustrates how different countries and industries are able to address climate change financial challenges, which are influenced by their economic status. However, the sign and the amount of this impact are always debating among researchers.

Additionally, Pankratz et al. [2023] and Addoum et al. [2023] examined the relationship between analyst forecasts and earnings announcements surprises with heat exposure. It was found by Pankratz et al. [2023] that announcement returns become negative with increasing heat exposure. They find that analysts and investors are not fully aware of the effects of high temperatures, and this effect is strongest after two quarters. Nevertheless, Addoum et al. [2023] indicate that in the US, analysts account for temperature shocks in most industries. There are, however, some industries in which temperature shocks can result in earnings surprises. Finally, they found that analysts' forecasts and stock prices do not respond immediately to observable intra-quarter temperature shocks.

There is also a specific area of behavioral finance research that examines how meteorological factors such as sunlight and daily temperature, cloud cover, or generally things referred to as weather instead of climate, affect investors' decisions in addition to the climate literature we discussed. In their study, Cao and Wei [2005] found that higher temperature is inversely related to stock returns in different markets duo to investors' apathy, and colder weather may encourage investors to be more aggressive and take more risks, which may result in a higher stock return. A key contribution of this study is to emphasize how environmental factors, such as temperature, may influence the behavior of investors and market dynamics. Hirshleifer and Shumway [2003] conducted a study that examined the relationship between sunny weather and stock returns in 26 countries. As a result, they suggest that sunlight may have a positive effect on investor mood as well as market performance. The findings are consistent with a broader understanding of how weather and mood influence decision-making. Saunders [1993] supports this viewpoint by demonstrating the correlation between sunny weather and increased stock prices in New York City. As a result, investor attitudes, which are affected by weather conditions, have a significant impact on market movements. The study conducted by Kamstra et al. [2003] on Seasonal Affective Disorder (SAD) and its impact on stock market returns illustrates how changes in investor mood are influenced by daylight variations. This suggests a seasonal trend in stock returns connected to mood fluctuations. This research challenges the idea that financial markets are purely dependent on logical decision-making, suggesting that changes in mood caused by weather might have significant impacts on these markets. All these studies indicate that sunlight and temperature are closely related. This means that behavioral financial studies of weather can have a close relationship with climate risks literature, and they can be studied together. According to most behavioral papers, the impact of the temperature on investor sentiment is analysed through the location of exchanges. I consider this as a means to assess the impact of temperature on investor sentiment.

Moreover, I perform a comprehensive review of heat-sensitive industries, in light of their crucial role as emphasized in studies related to climate change. Numerous studies have examined the impact of extreme temperatures on labor productivity and sales in these industries. For example, a study conducted by Zivin and Neidell [2014] in the US found that employees in companies in so-called climate-exposed industries affected by heat lower their working hours on days when the maximum daily temperature exceeds 85°F. Instead, they choose for indoor leisure activities. This behavior indicates a significant decrease in worker productivity because of high temperatures. Furthermore, Schlenker and Roberts [2009] specifically examine the influence of temperature on agricultural output, providing strong evidence of the negative effects of climate change on agriculture, especially in the US. This study demonstrates that although agricultural yields may initially rise when temperatures rise, they significantly decrease after certain thresholds are exceeded. Fisher et al. [2012] found that most pieces of evidence indicate that climate change could have a severe impact on the US agriculture industry, as it is highly affected by temperature and precipitation. In more recent studies, such as those by Addoum et al. [2020] and Addoum et al. [2023] a comprehensive analysis is done for the effect of high temperature exposure on establishment and firm level sales and productivity of these industries. Addoum et al. [2023] test whether the magnitude of extreme temperature has a different effect on firm profitability between heat-sensitive and non-heat-sensitive industries. They found that heat-sensitive industries show more sensitivity to extreme temperatures. However, Addoum et al. [2020] find no evidence that temperature extremes have a significant impact on establishment sales in heat-sensitive industries in the US. So, these literature highlights the significance of high temperature impact on heat-sensitive industries such as agriculture.

In my study, I include precipitation as a control variable since many leading studies have not included precipitation as an independent variable. For example, Jones and Olken [2010] found that precipitation has a less pronounced impact on exports than temperature, and this effect is not robust. As Dell et al. [2012] acknowledge, precipitation does have a mild effect on national growth, but most of the effects of precipitation in rich countries are largely attributed to very large outliers. According to Dell et al. [2014], precipitation may not have a significant impact on economic activity as temperature changes. The study by Addoum et al. [2020] included precipitation as a control variable, indicating it played a secondary role in the context of the effect of temperature on the performance of firms. Additionally, Pankratz et al. [2023] focus primarily on temperature, leaving a gap in the literature regarding precipitation's direct impact on financial performance. There is a complex picture in the existing literature, which indicates that precipitation impacts firm performance differently by region and industry, with some industries experiencing significant interaction effects with precipitation levels. However, the direction of these effects—whether positive or negative—remains unclear. Moreover, the studies by Saunders [1993], Hirshleifer and Shumway [2003], Kamstra et al. [2003], which extend this inquiry into behavioral finance, suggest temperature has a broader impact on investor behavior, but they do not include precipitation's effects and incorporate it as a control variable. Since precipitation has a complex influence on economic and financial variables, I also include it as a control variable.

The impact of temperature on the economic parameters is always a subject of debate. There are opposing opinions on how temperature affects stock market dynamics and what causes this effect. In Makridis and Schloetzer [2022], they find that the effect of sentiment spread into asset prices and stock returns become negative on very cold days or very hot days. So, they suggest that the increase in climate fluctuation can increase non-fundamental risk in the market. They announce that extreme local temperatures affect people beliefs beyond its effect on the firm or local level economic variables. However, based on the findings of Apergis [2023], high temperatures negatively impact global stock prices, and this impact can be attributed to the effects of high temperatures on firms' assets, investments, and leverage costs.

This study fills a significant gap in the literature by investigating the effects of monthly temperature anomaly fluctuation, which is the magnitude of deviation from long-run average, on stock return and volatility, particularly for heat-sensitive industries such as agriculture, mining, transportation, utilities, and construction. Specifically, this study investigates whether US firms' stock, as assets in an advanced country, is affected by temperature variation, and whether this is due to climate effects on firm parameters or weather effects on investor sentiment.

The work of Winter and Kiehl [2022] supports the idea of using temperature anomalies. According to these findings, temperature anomalies provide a more accurate reflection of ongoing shifts in climate patterns than static averages. As a result of anomalies, extreme weather events are occurring more frequently and with greater intensity, resulting in immediate and severe economic consequences. By contrast, average temperatures may overlook these critical fluctuations and their consequences. In order to re-adapt when societies deviate from these historical norms, substantial costs must be incurred. In order to cope with extreme weather conditions, these costs include modifying infrastructure, altering agricultural practices, and implementing new health measures.

My research differs from existing studies in two ways. First they consider temperature shocks as the number of days above or below a specific threshold such as Addoum et al. [2020] and Pankratz et al. [2023] that focus on extreme temperature events. And second, they have examined how temperature affects firm performance like sales or labor productivity or how equity analysts react to high temperatures. Among these studies, the amount of temperature anomaly as an indicator of climate variability has not been directly examined in relation to the return and risk of the US stock market.

There is no doubt that market dynamics are closely related to investor sentiment. most the studies examine the issue from the perspective of behavioral finance, focusing on variables related to weather, such as sunshine and cloud cover, which affect investors' moods, rather than assessing climate variables as environmental risks.But, I am taking one more step forward in combining the effects of temperature variations in exchange cities on investors' mood with climatic impacts on firms' infrastructures, and determining if potential changes in US public companies' return and risk are the result of climate risks or investor sentiment.

The reason for the use of climatic variables to assess the impact of climate risk on the stock market via its effects on the headquarters and firms' infrastructures is based on the Efficient Market Hypothesis in Fama [1970]. It states stock prices take into account all available information. Based on this, we examine the effects of temperature shocks on stock returns and risks in firms' headquarters.

Furthermore, among these climatic and behavioral studies, less research examines market volatility as well as return. Narayanamoorthy et al. [2015] investigated the weather's effect on stock volatility in India, using GARCH models. They found that temperature affects stock returns in some cities and volatility has an effect in some others. The authors emphasize that volatility should be taken into account when analyzing the relationship between weather conditions and financial markets. In addition, Kathiravan et al. [2017] found that weather, specifically temperature, affects stock market returns and volatility in Indian cities. For their analysis, they used different statistical tools, such as descriptive statistics, the ADF test, and GARCH (1, 1) models.

In a study by Tzouvanas et al. [2019] they used conditional value at risk to examine the impact of temperature fluctuations on systemic risk in European firms. They find that temperature variations have a significant effect on systemic risk, with higher temperatures increasing risk and cold shocks decreasing it. The research supports the idea that temperature affects systemic risk asymmetrically, with hot and cold shocks having nonlinear effects on the financial system. Despite some deviations among industries, the findings overall suggest that temperature variations play a significant role in influencing systemic risk in European firms.

Consequently, in order to provide a comprehensive analysis of the effects of the temperature anomaly on US stock markets, and since these advanced models are complex and outside the scope of this research, I evaluate the monthly standard deviation of daily returns as a proxy for volatility in both headquarters and exchanges.

I believe that the results of my research could be beneficial for portfolio management and investment decisions in relation to hedging against climate risk. Alekseev et al. [2022] proposes a method for building portfolios with a hedge against climate change risks based on a quantity-based approach. This quantity-based approach outperforms traditional methods and can also be applied to hedge against other types of risks, such as aggregate unemployment and house price risk. A study by de Palma and Prigent [2008] concludes that new types of options that combine equity and environmental assets should be used to hedge global environmental risks, in contrast to the current practice of creating separate option markets. In Engle et al. [2020], they emphasize the importance of hedging against climate change news. The study demonstrates the importance of adjusting investment portfolios to account for climate risks, emphasizing the critical importance of financial strategies that consider environmental factors.

Additionally, high temperatures have significant social and policy impacts, especially in the context of occupational heat stress. Nunfam et al. [2018] and Nunfam et al. [2019] emphasize the importance of investing in policies to combat occupational heat stress, emphasizing the importance of financial resources and research. Further, Kjellstrom et al. [2020] highlights the economic and social factors that contribute to health risks in hot workplaces, including gender-based employment and migrant workers' vulnerabilities. Spector and Sheffield [2014] recommends developing practical and universal approaches to assess and control occupational heat stress, particularly in middle- and low-income tropical and subtropical regions.

Due to the withdrawal of the United States from the Paris Climate Agreement, this research is essential for investment management and policymakers to gain a better understanding of investor reaction to high temperatures.

2 Hypotheses

According to the literature, an increase in extreme heat can negatively affect the economy by reducing labor supply, GDP and exports. This is particularly true in sectors highly exposed to climate conditions. Pankratz et al. [2023] discovered that heat negatively impacts firm performance. Addoum et al. [2020] do not find any significant effects of high temperatures on sales and labor productivity at the establishment level, including heat-sensitive industries. However, according to Addoum et al. [2023], this relationship is "bidirectional," meaning that high temperatures benefit some industries but are harmful to others. These climatic literature look at temperature shocks in two ways. Some studies investigate the effect of temperature above a certain level and others examine the effect of temperature below a certain threshold. They claim that temperatures above 30°C negatively affect performance, citing studies such as Pilcher et al. [2002] and Seppanen et al. [2006].

3 Data and methodology

A comprehensive dataset comprising climate and financial variables is used to study the impact of temperature anomaly on stock returns and volatility. In this section I will introduce the data sources, variables, and methodology we use to analyze the relationship between temperature anomaly and financial market dynamics.

Furthermore, the results of the behavioral papers are also somewhat complicated. Cao and Wei [2005] hypothesized that lower temperatures are associated with higher returns, whereas higher temperatures may lead to higher or lower returns. However, at both lower and higher temperatures, returns can be associated with aggression and risk taking. Furthermore, studies such as Hirshleifer and Shumway [2003] analyse parameters such as sunshine, which differ from temperature.

In general, the conclusions of all these studies differ and are very controversial, as Fisher et al. [2012] notes that economists cannot agree on the magnitude or even the sign of climate change's impact on agriculture production.

However, my research, which focuses on evaluating temperature anomalies, or deviations from the mean which is similar to the term abnormal temperature in Ongena and Özlem Dursun-de Neef [2024], cannot be hypothesized as they can, since the means of temperature vary from place to place and season to season. It is possible that in some locations and seasons, experiencing a temperature level above or below the mean may be a positive parameter or vice versa. Similarly, Addoum et al. [2020] assert that economic agents tend to adapt to local conditions and I see different results in places that are generally hotter or colder. In addition, as many literature state about the complexity of temperature direction interpretation, I hypothesize:

1. More deviation from the temperature mean in terms of magnitude affects stock returns (or standard deviation).
2. More deviation from the temperature mean in terms of magnitude affects stock returns (or standard deviation) in heat sensitive industry.

Table 1: Summary statistics

	Mean	1st quartile	Median	3rd quartile	SD
Return	-0.003	-0.055	0.001	0.055	0.269
Standard Deviation	0.04	0.01	0.02	0.04	0.10
Exchange mean	2.16	0.78	1.74	2.99	1.85
Exchange maximum	7.17	5.39	7.13	8.88	2.87
Exchange minimum	5.98	4.33	6.09	7.53	2.64
Exchange precipitation	1.53	0.50	1.18	2.06	1.44
City mean	2.54	0.91	1.93	3.52	2.27
City maximum	10.26	7.35	10.07	13.00	4.25
City minimum	9.47	6.78	9.26	11.95	4.14
City precipitation	1.49	0.47	1.09	2.03	1.51
Different cities	0.90	1.00	1.00	1.00	0.30
Heat sensitive	0.37	0.00	0.00	1.00	0.48
SP500	0.79	-1.77	1.26	3.60	4.44
VIX	2.25	-12.12	-0.60	10.93	22.70

Summary statistics are presented in this table for key variables in the study. Return is the monthly log return of the 18043 US public firms located and traded within the US continental borders. Standard deviation is the monthly standard deviation of daily returns for these firms. There are several variables for temperature anomaly in the city of exchange and city of headquarters starting with "Exchange" and "City" respectively, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month in reporting in Fahrenheit. SP500 and VIX are the monthly log returns of these two indices. Different cities is the dummy variable for firms traded in a different city rather than their headquarter city. Heat sensitive is another dummy variable for firms in industries identified as heat-sensitive by Zivin and Neidell [2014].

3.1 Data description

3.1.1 Financial Data

In order to obtain financial data, I utilize Compustat dataset to download the daily stock prices of 18043 companies from 1995 to 2024 located and traded in the US. It is aligned with other literature's time periods, which allows us to compare our results with theirs. I also download information about each company, such as headquarters cities, exchange codes, etc. As well as getting the industry code, I also use two classifications, NIACS and GICS. I decided to use NICAS due to its focus on North America and fewer missing values, which is an ideal match for the scope of my research.

Using daily stock prices I calculate the monthly log returns for all the firms, S&P500 and VIX. I calculate monthly standard deviation of the daily log returns as a proxy for volatility.

To clean the raw dataset which is for all the firms' stock prices in North America I first download a comprehensive list of US cities from Simplemaps.com, and then remove all of the other cities that are in Canada or outside of the continental US. Then to keep the firms listed on major exchanges in the US I use the most significant exchange codes located in the cities of New York, Chicago and Philadelphia.

3.1.2 Climate Data

In terms of climate information, PRISM, the US Department of Agriculture's official climatological database, provides temperature and precipitation information. In the PRISM datasets, maximum, minimum, and mean temperatures are provided for daily and monthly intervals, as well as precipitation levels for 4*4 km or 800*800 m grids.

To download the time series climatic data from PRISM I need the latitude and longitude of each location. In order to obtain an approximate location of each city and not the exact address of each firm, I use Simplemaps.com to obtain the latitude and longitude of each city. In contrast to Pankratz et al. [2023] or Addoum et al. [2020], which utilize precise location data for firm headquarters, my approach utilizes city-wide averages for temperature and precipitation. The decision was influenced by practical considerations such as data complexity and evolving work patterns especially after COVID lockdown, including remote working, which reduce the significance of a firm's specific geographical location.

I use location data to get monthly climate records for the given period. While Addoum et al. [2020] and Pankratz et al. [2023] look at the number of days that surpass a particular threshold, my analysis will look at how big deviations from the long-term average are, providing a different perspective on how they affect risk and return. To begin with, I calculate a 30-year moving average using the monthly mean temperature (e.g. last 30 Januaries). Then for all maximum, minimum and mean monthly temperatures in each location I compute the absolute value of deviation from the 30-year mean. It is necessary to calculate the size of deviation for Maximum and Minimum temperatures to assess the impact of extreme deviations as well as average deviations. Minimum and maximum temperature anomalies can be interpreted as extreme cold and hot anomaly with respect to the 30-year MA respectively. In addition, To calculate the precipitation anomaly, the same procedure is followed for the rainfall monthly level.

Finally, I match each firm's city with its temperature and precipitation anomaly in a given month to understand how much deviated a given month temperature in a city is in comparison to its historical norms for that specific month. Additionally, these climate data are mapped to the cities where the trading exchanges are located in order to provide temperature and precipitation anomalies for the cities where the stocks of firms are traded.

Table 1 presents summary statistics for financial and climate variables. It displays the mean, standard deviation, median, first and third quartiles. Temperatures are in Fahrenheit degrees, and precipitation is measured in inches. The words "mean", "minimum" and "maximum" each shows its deviation from the 30-year average. The column "mean" for dummy variables shows the percentage of those dummies among all the firms.

3.2 Methodology

According to the climate economic literature, I use the following panel data regression to test the relationship between temperature anomaly and monthly return or standard deviation:

$$\text{Return}_{i,j,t} = \theta_i + \theta_{j,t} + \beta_1 \text{T}_{i,t} + \beta_2 \text{P}_{i,t} + \beta_3 \text{SP500Return}_t + \epsilon_{i,j,t}$$

$$\text{Standard Deviation}_{i,j,t} = \theta_i + \theta_{j,t} + \beta_1 \text{T}_{i,t} + \beta_2 \text{P}_{i,t} + \beta_3 \text{VIX}_t + \epsilon_{i,j,t}$$

Here $\text{Return}_{i,j,t}$ is the log return for firm i, in industry j during month t. $\text{T}_{i,t}$ are the temperature anomalies for Mean, Maximum and Minimum temperature during month t in the cities of headquarter and exchange of firm i. Further, $\text{P}_{i,t}$ represents precipitation anomalies as control variables in the city of the firm's headquarters and the city of its exchange.

In order to control for time-invariant unobserved heterogeneity among firms, I incorporate the firm fixed effect (θi). Similar to Pankratz et al. [2023] and Addoum et al. [2020], an industry-year fixed effect ($\theta_{j,t}$) is used control for technical advancements and trends within each specific industry throughout the year.

Moreover, I have included two dummy variables in the interaction terms:

1. (×Heat Sensitive): represents a dummy for heat sensitive industries. Zivin and Neidell [2014] and Addoum et al. [2020] provide the list of industries. The industries are Agriculture, Forestry, Fishing and Hunting (first two digits are 11), Mining (21), Utilities (21), Construction (23), Manufacturing (31-33), and Transportation (48-49).
2. (×Different City): As discussed in the introduction, there are two groups of literature related to my research, behavioral and climate finance. I combine these two criteria and assess the behavioral aspect of climate change by adding an interaction term which is for the temperature of the city of exchanges. This indicates that a company's headquarter is located in a different city from the city in which its stock is traded. It is to avoid using the headquarters' city temperature twice if the headquarters and exchange are in the same city.

Moreover, I do not need to control for seasonality of temperature, because I am analyzing the impact of temperature anomaly which is the deviation from the 30-year average of each month and is compared with its own month long-run mean.

Additionally, I control for the general trends in market by incorporating SP500 return as a market proxy for stock return. In addition, I control the effect of the VIX index as a proxy for market volatility.

I do not include other control firm-related variables as Dell et al. [2014] and Angrist and Pischke [2008] indicate that controlling for firm-level time-varying characteristics will not necessarily make a more precise estimate because these variables may change themselves during time with the effect of the main independent variable (temperature anomaly).

Standard errors are double clustered in time and entity for both return and standard deviation to adjust for the potential heteroskedasticity and serial correlation in panel data based on the Addoum et al. [2020] that finds double clustering is more conservative.

4 Main Empirical Tests and Results

4.1 Do temperature anomalies affect monthly return?

Table 2: Effect of temperature anomaly on return

	A. Return								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Headquarter	9.828e-05 (0.2322)						-0.0003 (-0.8732)		
Max Headquarter		-6.627e-05 (-0.2371)						-0.0002 (-0.8589)	
Min Headquarter			-0.0003 (-1.0306)						-0.0003 (-1.3291)
Mean Exchange				0.0010 (1.1665)					
Max Exchange					0.0002 (0.3649)				
Min Exchange						-9.479e-05 (-0.1552)			
Mean Exchange × Different							0.0013 (1.4309)		
Max Exchange × Different								0.0004 (0.6159)	
Min Exchange × Different									4.254e-05 (0.0713)
Precipitation Headquarter	-0.0003 (-1.2386)	-0.00031 (-1.3064)	-0.0004 (-1.5706)				-0.0003 (-1.5999)	-0.0003 (-1.6492)	-0.0004 (-1.6689)
Precipitation Exchange				-0.0002 (-0.2922)	-0.0002 (-0.3014)	-0.0003 (-0.3149)			
Precipitation Exchange × Different							-0.0001 (-0.1783)	-0.0001 (-0.1454)	-0.0002 (-0.1796)
SP500	0.0096 (17.839)	0.0096 (17.949)	0.0096 (17.924)	0.0096 (17.385)	0.0096 (17.659)	0.0096 (17.753)	0.0096 (17.456)	0.0096 (17.697)	0.0096 (17.774)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0283	0.0283	0.0283	0.0283	0.0283	0.0282	0.0283	0.0283	0.0283
No. observations	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043	18043	18043	18043

Table 2 reports the impact of different temperature anomaly measurements on US firms' return. The dependent variable is log return. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. There are also interaction terms for those firms that their exchanges are in different city than their headquarters. $t - statistics$, reported below coefficient estimates in parentheses, are calculated using double clustering standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

The first issue that I address is whether temperature anomalies have an impact on public companies' stock return in the US. In Table 2, I present the results of various regressions based on my primary model, enabling a comprehensive interpretation of the question.

In column 1, the deviation of the monthly mean temperature from the 30-year moving average (MA) at the headquarters city is regressed on the firm's log return. The coefficient is very small and statistically insignificant.

The results for columns 2 and 3, which assess the impact of the temperature anomaly based on maximum and minimum monthly temperatures that show the extreme deviations in each month, respectively, are statistically insignificant and not different from zero.

In columns 4, 5, and 6, I evaluate the effects of mean, maximum, and minimum monthly temperature anomalies in the cities where firms' stocks are traded. Similar to headquarters' cities, these results are statistically insignificant. However, the t-statistics of mean temperature anomaly in column 4 is notable in comparison with others. it shows that 1 degree Fahrenheit increase in the magnitude of monthly mean temperature deviation form 30-year MA increase the return by 0.0010 percent.

The columns 7, 8 and 9 are examining another aspect of our research, namely determining the effect of temperature anomalies in the city of headquarter and exchange in one equation by adding a dummy variable interaction term for firms with their headquarters and exchanges in different cities. Also, none of them show a significant result at a 1, 5 or 10 percent level of significance. These results indicate that the long run temperature deviation may not be a good measure for investors mood, and focusing on daily variables such as sunshine, cloud cover, daily temperature or in other words the weather variables not the climatic measures, can be a better predictor.

Overall, I did not find a statistically significant result different from zero. This indicates that different temperature anomalies in public companies' headquarters or exchanges have no impact on monthly returns. This results are matched with those climate economic literature that find no significant relationship between temperature and economic parameters in US.

4.2 Do temperature anomalies affect monthly standard deviation?

In this chapter, I explore whether temperature anomalies affect US public companies' stock returns standard deviation. Table 3 presents the results of various regression analyses based on the main model.

The deviation of the monthly mean temperature from the 30-year moving average (MA) in the headquarters city is regressed upon the monthly standard deviation of the firm's returns in column 1. Although the coefficient is statistically insignificant, it is very notable with t-statistics of 1.60. It shows an increase in mean temperature anomaly in headquarter by 1 degree Fahrenheit increases the standard deviation of firms stock by 0.0017 points.

Statistically insignificant result is obtained for columns 2, which assess the impact of temperature anomalies based on maximum monthly temperatures.

The coefficient of the monthly minimum temperature anomaly for the headquarters is significant at the 10 percent significance level. The table indicates that if the deviation of the monthly minimum temperature from the 30-year average in the headquarters increases 1 degree Fahrenheit, the standard deviation in the headquarters decreases by 0.0011 points.

The effect of temperature in the exchange city on volatility is estimated by regressing the mean, maximum, and minimum temperature anomalies on the monthly standard deviation. The coefficient of monthly mean

Table 3: Effect of temperature anomaly on standard deviation

	Standard Deviation								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean Headquarter	0.0017						0.0009		
	(1.6002)						(1.4356)		
Max Headquarter		0.0005						4.611e-05	
		(1.1031)						(0.1734)	
Min Headquarter			-0.0011*						-0.0006*
			(-1.9084)						(-1.7275)
Mean Exchange				0.0032*					
				(1.6888)					
Max Exchange					0.0014				
					(1.5328)				
Min Exchange						-0.0021*			
						(-1.8100)			
Mean Exchange × Different							0.0028*		
							(1.6769)		
Max Exchange × Different								0.0014	
								(1.5924)	
Min Exchange × Different									-0.0018*
									(-1.7136)
Precipitation Headquarter	0.0002	0.0001	-0.0001				9.652e-05	1.238e-05	-0.0001
	(1.3045)	(0.9900)	(-1.0380)				(0.8136)	(0.1256)	(-0.8428)
Precipitation Exchange				-0.0003	-0.0003	-0.0005			
				(-0.4866)	(-0.5157)	(-0.8433)			
Precipitation Exchange × Different							-0.0002	-0.0003	-0.0005
							(-0.4018)	(-0.5068)	(-0.8111)
VIX	-7.155e-06	-1.849e-05	-2.039e-05	1.791e-06	-1.631e-05	-2.737e-05	3.025e-06	-1.669e-05	-2.6e-05
	(-0.2015)	(-0.5482)	(-0.5952)	(0.0464)	(-0.4656)	(-0.7238)	(0.0779)	(-0.4802)	(-0.6970)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0019	0.0004	0.0018	0.0045	0.0021	0.0038	0.0046	0.0019	0.0042
No. observations	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043	18043	18043	18043

Table 3 reports the impact of different temperature anomaly measurements on US firms' standard deviation. The dependent variable is standard deviation respectively. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. There are also interaction terms for those firms that their exchanges are in different city than their headquarters. $t - statistics$, reported below coefficient estimates in parentheses, are calculated using double clustering standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

temperature anomaly in exchange is statistically significant at a significance level of 10 percent in column 4. As a result, a 1 degree Fahrenheit increase in the absolute value of monthly mean temperature deviation from long-run average can result in an increase of 0.0032 points in standard deviation. However, the results in column 5, which pertains to the maximum temperature anomaly in exchange, are not significantly different from zero.

In column 6, the coefficient shows that an increase in minimum temperature anomaly in exchange by 1 degree Fahrenheit can reduce the standard deviation by 0.0021 points. The coefficient is significant at 10. This result is similar to the coefficient of the minimum temperature anomaly in the headquarters in column 3.

By using dummy interaction terms to evaluate the headquarters temperature anomaly in one equation with the exchange temperature anomaly, in column 7 I find statistically significant results at 10 percent significance level for the coefficient of the interaction term (Mean Exchange × Different), confirming our result in column 4. Based on it, a 1 degree increase in mean temperature anomalies in exchange cities will increase the standard deviation by 0.0028 points for companies whose headquarters are not located in the same city as their exchanges.

According to column 8, the influence of the maximum temperature anomaly in headquarters and the (Max Exchange × Different) interaction term on the standard deviation of US firms' stock returns is statistically equal to zero.

In column 9, It is shown that both the minimum temperature anomalies in headquarters and the interaction term (Min Exchange × Different) are statistically significant at the 10 percent level of significance. In both headquarters and exchange, a 1 degree Fahrenheit increase in the magnitude of the monthly minimum temperature deviation from the 30-year average can result in a 0.006 and 0.0018 point decrease in the standard deviation, respectively.

The coefficients associated with the headquarter and exchange mean temperature anomaly in column 1 and 4, and the interaction term (mean exchange x difference) in column 7 are positive. Because of the fact that the mean temperature anomaly measurement cannot be used to determine the direction or sign of the change in temperature anomaly, it indicates that the deviation from the long-run average of the monthly mean temperature increases the standard deviation, which is due to shocks to climatic adaptation based on the previous literature.

On the other hand, the coefficients related to minimum temperature anomaly in the headquarter, the exchange and the interaction term (Min Exchange × Different) are negative. It can be concluded that if it becomes colder with respect to the 30-year monthly average, the standard deviation will decrease. These are aligned with the findings of Tzouvanas et al. [2019] which found that cold shocks can decrease systematic risks.

Overall, the t-statistics for standard deviation are higher than those for return. This indicates that deviation from the long-run average of monthly mean, maximum and minimum temperatures may be a better indicator of volatility than return. Further, both the headquarter and the exchange display similar results, suggesting that the monthly stock standard deviation in the United States is sensitive to the effects of temperature variability via both investor sentiment and climate risk impacts on the firms' infrastructure.

4.3 Heat sensitive industries

In order to isolate the effect of the temperature anomaly on heat-sensitive industries identified by Zivin and Neidell [2014], I use an interaction term between the heat-sensitive dummy and the climatic variables. Several regressions are run for mean, maximum, and minimum anomalies in both headquarters and exchange cities. Having a better understanding of the performance effect of firms and investor sentiments on financial market dynamics in these specific industries is an important factor behind this idea.

4.3.1 Return

Panel A in Table 4 shows regressions evaluating these impacts on US firms' returns operating in these industries. In column 1, I do not find significant results for monthly mean temperature anomaly in headquarters cities. Using maximum and minimum temperature anomalies respectively, columns 2 and 3 are statistically equivalent to zero for heat-sensitive industries.

In columns 4,5 and 6, the climate variables of the exchanges' cities do not produce significant results. The only notable result is the t-statistic (1.60) of the interaction term between the monthly mean temperature anomaly in exchange and the heat-sensitive dummy. This shows that a 1 degree Fahrenheit increase in the magnitude of monthly mean temperature deviation from the 30-year moving average can increase return by 0.0009 percent, which is not statistically and economically significant.

Generally, my hypothesis which claims that the absolute value of the monthly temperature anomaly significantly affects the return of US firms stock in heat-sensitive industries is not supported by empirical evidence.

4.3.2 Standard deviation

In Table 4, Panel B shows the effect of temperature anomalies on the monthly standard deviation of US firms' stock in the heat-sensitive industries. The heat-sensitive interaction term is statistically significant at a 5 percent significance level in column 7. In heat-sensitive industries, the monthly standard deviation of the firms' returns increases by 0.0003 points if the temperature anomaly increases by 1 degree Fahrenheit.

Using maximum temperature anomaly for both headquarters and exchanges, in columns 8 and 11, there are no significant results for their variables and their interaction terms.

The coefficients of the minimum temperature anomaly in the headquarters and its interaction term with the heat-sensitive dummy are statistically significant at 10 and 5 percent significance levels, respectively, in column 9. Increases of 1 degree Fahrenheit in the minimum temperature anomaly decrease the standard deviation by 0.00010 points in industries that are not heat-sensitive and by 0.0003 points in industries that are heat-sensitive.

A notable finding regarding temperature deviation in the exchanges can be found in columns 10 and 12, where the mean temperature anomaly and minimum temperature anomaly show significant results at the 10 percent level in non heat-sensitive industries but no significant results in heat-sensitive industries. Column 10 indicates that a 1 degree Fahrenheit increase in the mean temperature anomaly in the exchanges increases the standard deviation of the non-heat sensitive industries by 0.0028. Additionally, a 1 degree Fahrenheit increase in the minimum temperature anomaly in the exchanges decreases the standard deviation of the firms in non-heat-sensitive industries by 0.0019 points. In both cases, these results demonstrate the effectiveness of temperature shocks on investor moods in exchange cities, regardless of the type of industry involved.

However, in the headquarters, the results are more noticeable for heat-sensitive industries as compared to non-heat-sensitive industries. It means that temperature anomaly in the headquarter have an impact on the standard deviation of heat-sensitive industries. In other words, it shows that stock market standard deviation is sensitive to the impact of temperature anomaly on heat-sensitive industries via their headquarter and firms' infrastructure channels.

Similarly to table 3, measurements using minimum temperature have negative coefficients and measurements using mean temperature have positive coefficients, but maximum temperatures are not significant. Furthermore, The strength of being significance at 5 percent level for the heat-sensitive coefficients in column 7 and 9 in comparison with the non heat-sensitive show the sensitivity of firms in heat-sensitive industries to the temperature anomaly which is shown in their stock standard deviation.

In summary, our hypothesis that the absolute value of the monthly temperature anomaly significantly affects the standard deviation of US firms in heat-sensitive industries has been supported by some empirical evidence.

Table 4: Effect of temperature anomaly on return of heat-sensitive industries

	A.Return						B.Standard deviation					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Mean Headquarter	-2.04e-05						0.0015					
	(-0.0516)						(1.5674)					
× Heat Sensitive	0.0003						0.0003**					
	(1.0778)						(1.9990)					
Max Headquarter		-0.0001						0.0005				
		(-0.4115)						(1.1566)				
× Heat Sensitive		0.0001						1.489e-05				
		(0.6397)						(0.2043)				
Min Headquarter			-0.0002						-0.0010*			
			(-0.6563)						(-1.8471)			
× Heat Sensitive			-0.0004						-0.0003**			
			(-1.4122)						(-2.0509)			
Mean Exchange				0.0007						0.0028*		
				(0.9121)						(1.6872)		
× Heat Sensitive				0.0009						0.0008		
				(1.6017)						(1.6240)		
Max Exchange					0.0002						0.0013	
					(0.3061)						(1.5499)	
× Heat Sensitive					0.0002						0.0004	
					(0.4221)						(1.4376)	
Min Exchange						-0.0002						-0.0019*
						(-0.4310)						(-1.8028)
× Heat Sensitive						0.0003						-0.0006
						(0.7749)						(-1.6360)
Precipitation Headquarter	-0.0004	-0.0004	-0.0004				0.0002	0.0001	-7.753e-05			
	(-1.5740)	(-1.6119)	(-1.7040)				(1.3010)	(1.0670)	(-0.6436)			
× Heat Sensitive	0.0002	0.0001	4.925e-05				3.952e-05	1.23e-05	-0.0001			
	(0.4647)	(0.4336)	(0.1455)				(0.3331)	(0.1027)	(-0.8530)			
Precipitation Exchange				-0.0004	-0.0004	-0.0004				-0.0002	-0.0002	-0.0004
				(-0.5690)	(-0.5789)	(-0.6072)				(-0.3629)	(-0.4047)	(-0.7530)
× Heat Sensitive				0.0004	0.0004	0.0004				-0.0002	-0.0002	-0.0003
				(0.6179)	(0.6056)	(0.6675)				(-0.8584)	(-0.8153)	(-0.9862)
A.SP500 - B.VIX	0.0087	0.0087	0.0087	0.0086	0.0086	0.0086	-5.157e-06	-1.522e-05	-1.746e-05	2.601e-06	-1.377e-05	-2.401e-05
	(16.504)	(16.623)	(16.619)	(15.994)	(16.295)	(16.399)	(-0.1587)	(-0.4912)	(-0.5539)	(0.0733)	(-0.4262)	(-0.6860)
× Heat Sensitive	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026	1.368e-06	-1.636e-06	-8.897e-07	3.929e-06	-5.766e-07	-3.135e-06
	(8.1685)	(8.1651)	(8.1701)	(8.0824)	(8.1551)	(8.2189)	(0.1206)	(-0.1467)	(-0.0788)	(0.3607)	(-0.0524)	(-0.2625)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0287	0.0287	0.0288	0.0288	0.0287	0.0287	0.0019	0.0004	0.0020	0.0048	0.0022	0.0042
No. observations	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043	18043	18043	18043	18043	18043	18043

Table 4 reports the impact of different temperature anomaly measurements on heat-sensitive industries. These industries are Agriculture, Forestry, Fishing and Hunting (first two digits are 11), Mining (21), Utilities (21), Construction (23), Manufacturing (31-33), and Transportation (48-49) with their codes in NIACS classification. The dependent variables in panel A and panel B are log return and standard deviation respectively. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. In each equation shown in columns, there is also an interaction term between these measures and the heat-sensitive industries dummy. The values in the row A.SP500 - B.VIX belong to SP500 if they appear in panel A, and to VIX if they appear in panel B. $t-statistics$, reported below coefficient estimates in parentheses, are calculated using double clustering standard errors for both firms and time. Significant results are specified by * (P-value $<$ 0.10), ** (P-value $<$ 0.05) and *** (P-value $<$ 0.01).

5 Robustness Checks

In this part, I conduct the final tests to assess the robustness of the baseline model. Firstly, to analyze how lagged temperature anomaly can affect the market dynamics. Secondly, assess how heterogeneous temperature sensitivities in warm and cold areas affect the model. Third, I use an industry-quarter fixed effect instead of a year-industry fixed effect in order to obtain a more detailed analysis of variations within a year.

5.1 Lagged Temperature Effect

In order to check the robustness of my main results, I use one-quarter lagged variables for different measures of temperature anomaly to examine both the immediate and lagged effects of temperature anomaly on return and standard deviation.

According to Pankratz et al. [2023], high temperatures can negatively affect firm performance one to two quarter after exposure. Barrot and Sauvagnat [2016] found that environmental shocks have both immediate and delayed effects on company performance. According to them, lagged variables are important when assessing the full impact of shocks.

Literature suggests that the market may not react immediately to temperature anomalies. Markets adjust themselves as firms release financial announcements and more information becomes available. These announcements are published quarterly, and the reports show the potential effects on temperature shocks. Further, as stated in Pankratz et al. [2023], analysts may become surprised with the announcements and update their forecasts.

According to Daniel et al. [1998], investors may under-react to new information due to cognitive biases, resulting in delayed market responses. As a result, the market may not react fully to a temperature anomaly immediately but may react more significantly as the effects become evident over time. As a result, these effects may be reflected in the stock market dynamics. These shocks often cause analysts and investors to adjust stock prices in the following quarters. Hence, it is important to understand both the immediate and lag effects of temperature anomalies on stock returns and standard deviations.

Table A1 in the appendix does not show a significant result, and they are in line with the main results, except for the coefficient of lag for the minimum temperature anomaly in column 6. As shown in the table, this result is significant at the 5 percent significance level and shows an increase of 1 degree Fahrenheit in the monthly minimum temperature deviation from the 30-year MA, increasing the return of the next quarter by 0.0005 percent.

According to this significant result, if the magnitude of the deviation of monthly minimums from the long-run average increases by one degree, this is likely to increase the stock return in the upcoming quarter.

Generally, the results of this test indicate that my main analysis is robust, and that there is a less significant relationship between monthly returns and one-quarter lags.

Table A2 in the Appendix provides the results of regressing the monthly standard deviation of US firms' stock returns on the temperature anomaly variables and their one-quarter lag.

It is shown that only the maximum temperature anomaly at the headquarters with one quarter lag is statistically significant at a significance level of 10 percent, and a 1 degree Fahrenheit increase in the magnitude of the deviation from the long-run average of monthly maximum can result in a 0.0003 point increase in the standard deviation. In addition, the coefficient of the one-quarter lag of the mean temperature anomaly in the exchange shows that an increase of 1 degree Fahrenheit can result in a decrease of 0.008 points in the standard deviation. Both of these coefficients, however, are economically negligible

Compared to table 3, the results of this analysis are less significant. It appears from these results that the deviations in monthly temperatures are more likely to affect the standard deviations immediately rather than to have a lagged effect, although those results are also considered to be of very low economic importance.

Overall, except for a few low results, most of the results show no one-quarter lagged effect for the monthly temperature anomalies.

5.2 Warmer location adaptation

According to Kotz et al. [2021], warmer regions and regions with low latitudes, as well as coastal regions, experience greater day-to-day temperature variability which is shown as intra-monthly standard deviation of daily temperatures. In these regions, marginal losses are the most significant as a result of increased temperature fluctuations. In general, they have a smaller seasonality and are less resilient to daily fluctuations in temperature. Accordingly, warmer locations can be more sensitive to within a month temperature anomalies than colder locations.

As in Addoum et al. [2020], I categorized the sample into warmer and colder locations. WhileAddoum et al. [2020] use half of the annual temperature averages in their study to determine warmer locations, I use the 100-year averages of temperatures of US cities from 1920 to 2020 to determine warmer locations which are above the median. I evaluated this idea using an interaction term using the different measurements of temperature anomaly in both headquarters and exchanges for return and standard deviation.

According to table A3, the log return of US firms is regressed on the different temperature anomalies including mean, maximum, and minimum in headquarters and exchanges, as well as their interaction terms with the dummy variable for warmer locations. According to the t-statistics of these interaction terms, there is no statistically significant result for firms located in warm climates. The only notable result is the coefficient of (Min Headquarter × Warmer) with a t-statistic of 1.23 although it is not significantly different from zeros.

In addition, I find that these tests produce similar to baseline regressions results for the monthly standard deviation. There are no significant results for the interaction coefficients of warmer locations in Table A4 in the appendix. Some notable results are the interactions between the warmer location dummy and the temperature anomalies in the headquarter variable. It should be noted their t-statistics are bigger than the t-statistics of the exchange temperature anomalies especially in maximum which could be an indicator for high temperature. However, they are not different from zero. Coefficients and t-statistics for the interaction term between warmer dummy and exchange temperature deviations are very low.

Therefore, the standard deviation of US firms' stocks can be more sensitive to temperature anomalies in headquarter than it is to exchanges. In light of this, investors in exchanges are not concerned whether the headquarters are located in warmer regions or not, since they are not involved in the operations of the headquarters.

Overall, I do not find any significant evidence to suggest that firms in warmer cities have different monthly returns and standard deviations from those in colder regions.

5.3 Quarter-Industry fixed effect

Since each industry within a year is subject to seasonality and short-term economic cycles, there can be a specific season for each industry, such as harvest time in agriculture, etc. It is possible that this variation can influence our interpretation of the effects of temperature anomalies in numerous industries. In order to capture the unobserved heterogeneity that differs by quarter and industry, I use a quarter-fixed effect. To do these regressions, I regress the log return and standard deviation of firms in our sample on different temperature anomalies in headquarters and also with the interaction terms of the exchange temperature variables with the dummy of different cities to account for those firms that have their headquarters and exchanges in different cities.

Additionally, in order to prevent confounding, I do not include the heat-sensitive industry dummy with the quarter-industry fixed effect. Heat-sensitive industries may experience unique temperature variations (e.g., consistently higher temperatures in certain seasons). The industry-quarter fixed effects may already account for some of the temperature effects I would like to explore with the heat-sensitive interaction terms.

Table A5 analyzes the impact of different temperature anomalies with different city dummy on US firms' log returns using quarter-industry fixed effects. Generally, the results of this study are similar to those in the main analysis, however the coefficients of the minimum temperature anomaly in headquarters are significant at 5 and 10 percent significance levels, respectively, in column 3 and column 6. These findings indicate that potential seasonal influences were not captured in the original model and may have been overlooked. Although the coefficients are statistically significant, their values are low and their directions are consistent with the results of the industry-year fixed effect regression.

Overall, the robustness check results including the alternative specification are consistent with the results of my primary model. This indicates that the main results and conclusions are robust, but should be interpreted with caution duo to the industry variations within a year.

Using a quarter-industry fixed effect, I analyze the effect of temperature anomaly on the monthly standard deviation of US firms in table A6. The results indicate an interesting pattern. In comparison to the year-industry fixed effect, the t-statistics of exchange temperature variables in columns 4,5 and 6 clearly increase. In column 3, the coefficient of the minimum temperature anomaly in headquarter is statistically significant at the 5 percent significance level, but it is not significant when it is combined with the minimum exchange temperature anomaly interaction term. Furthermore, the coefficient of the interaction term of maximum temperature anomaly in exchange has become significant, whereas it was not significant in the industry-year fixed effect model.

This shows that the seasonality of each industry has a more meaningful relationship with the headquarters temperature than the exchanges, because when we use the quarter-industry fixed effect to control this seasonality, the significance of the headquarters temperature anomalies results diminishes.

The results show the temperature impact of the headquarters is very seasonal and depends on the time of the quarter, but the temperature can impact investor sentiment in exchanges regardless of the industry's seasonality.

Both models are robust, but exhibit different levels of variability between headquarters and exchange temperatures. This depends on the essence of our research to assess the effect of the temperature anomaly on the stock return and standard deviations by accepting that seasonality exists in each industry or by controlling those seasonal patterns to conduct this analysis in an equal way without considering the extreme effects that can occur in different quarters.

6 Conclusion

My research examines how the deviation of the mean, maximum, and minimum monthly temperatures from the 30-year moving average of that month affects the return and risk of the US stock market. I assess the potential impact of the temperature anomaly on the US stock market dynamics based on its effects on the city of the headquarters, infrastructures, and labors, as well as its effects on the mood of investors captured by the city of the exchanges. In addition, I conduct this analysis for heat-sensitive industries.

Our results in most of the tests we conduct are consistent with those reported by Addoum et al. [2020]. I find that the relationship between temperature anomaly and return in both the headquarter and exchange is economically and statistically insignificant. This is also true for the return of firms operating in heat-sensitive industries.

However, I find that some measurements of temperature anomalies influence the monthly standard deviation of the stock return of US public companies. According to this study, the deviation of monthly minimum temperatures from their 30-year mean has a negative relationship with standard deviation in both headquarters and exchanges. These results indicate that cold shocks can decrease market standard deviation. Moreover, the deviation of monthly mean temperature as an temperature adaptation indicator from the long-run temperature average can increase the standard deviation due to the more variation it makes in the temperature.

A dummy of heat-sensitive industries enabled me to discover a finding. The results demonstrate the effectiveness of temperature shocks on investor moods in exchange cities, regardless of the type of industry However, in the headquarters, the results are more noticeable for heat-sensitive industries as compared to non-heat-sensitive industries. it shows that stock market standard deviation is sensitive to the impact of temperature anomaly on heat-sensitive industries via their headquarter and firms' infrastructure channels or in other word whether a firm is in a heat-sensitive industry or not does not affect its standard deviation in exchanges.

As a last resort, the results of this study can serve as a starting point for further research. It is possible to expand this idea more precisely with the aid of more advanced methods such as geocode, which allows us to find the exact coordinates of all firm properties, not only the headquarters but also all of the branches, etc. The effect of firms' branches spread across warm and cold geographical locations on their stock and profitability resilience against the changes in temperature is another new research idea to be explored.

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A Appendix

Table A1: Lagged Temperature Effect - Return

	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Headquarter	7.091e-05			-0.0003		
	(0.1650)			(-1.0859)		
Mean Headquarter$(t-3)$	0.0003			0.0003		
	(1.0259)			(1.1377)		
Max Headquarter		-8.084e-05			-0.0002	
		(-0.2868)			(-1.0256)	
Max Headquarter$(t-3)$		-2.537e-05			-1.136e-05	
		(-0.1120)			(-0.0573)	
Min Headquarter			-0.0003			-0.0003
			(-0.9744)			(-1.2778)
Min Headquarter$(t-3)$			0.0004			0.0005**
			(1.3887)			(2.0453)
Mean Exchange × Different				0.0013		
				(1.4304)		
Mean Exchange × Different$(t-3)$				0.0003		
				(0.3763)		
Max Exchange × Different					0.0004	
					(0.6069)	
Max Exchange × Different$(t-3)$					-5.29e-05	
					(-0.0973)	
Min Exchange × Different						0.0001
						(0.2042)
Min Exchange × Different$(t-3)$						-0.0004
						(-0.6954)
Precipitation Headquarter	-0.0003	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004
	(-1.2993)	(-1.3504)	(-1.6712)	(-1.6636)	(-1.7043)	(-1.6515)
Precipitation Headquarter$(t-3)$	0.0002	0.0002	0.0002	0.0001	0.0001	0.0002
	(0.7813)	(0.6577)	(0.9268)	(0.5663)	(0.4989)	(0.7922)
Precipitation Exchange × Different				-0.0001	-7.165e-05	-0.0001
				(-0.1264)	(-0.0846)	(-0.1235)
Precipitation Exchange × Different$(t-3)$				0.0009	0.0009	0.0009
				(0.8586)	(0.8456)	(0.8196)
SP500	0.0096	0.0096	0.0097	0.0096	0.0096	0.0096
	(17.927)	(18.003)	(18.041)	(17.515)	(17.805)	(17.929)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0289	0.0289	0.0290	0.0290	0.0290	0.0290
No. observations	1909202	1909202	1909202	1909202	1909202	1909202
No. firms	17749	17749	17749	17749	17749	17749

Table A1 reports the impact of one-quarter lagged temperature anomaly measurements on the monthly log return of US public firms' stock. The dependent variable is log return. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. In each equation shown in columns, There are also interaction terms for those firms that their exchanges are in different city than their headquarters. $t-statistics$, reported below coefficient estimates in parentheses, are calculated using double clustered standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

Table A2: Lagged Temperature Effect - Standard Deviation

	Standard deviation					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Headquarter	0.0015			0.0008		
	(1.4465)			(1.6872)		
Mean Headquarter$(t-3)$	-0.0002			0.0002		
	(-1.0990)			(0.8934)		
Max Headquarter		0.0004			8.395e-05	
		(1.0339)			(0.4248)	
Max Headquarter$(t-3)$		0.0002			0.0003*	
		(1.4046)			(1.6347)	
Min Headquarter			-0.0008			-0.0005
			(-1.5538)			(-1.6114)
Min Headquarter$(t-3)$			-7.423e-05			3.057e-05
			(-0.7435)			(0.2415)
Mean Exchange × Different				0.0019		
				(1.4203)		
Mean Exchange × Different$(t-3)$				-0.0008**		
				(-1.9682)		
Max Exchange × Different					0.0009	
					(1.3099)	
Max Exchange × Different$(t-3)$					-0.0003	
					(-1.1431)	
Min Exchange × Different						-0.0007
						(-1.1077)
Min Exchange × Different$(t-3)$						-0.0003
						(-1.1330)
Precipitation Headquarter	0.0001	7.019e-05	-0.0001	3.842e-05	-3.834e-05	-8.922e-05
	(1.0281)	(0.6663)	(-1.0358)	(0.4243)	(-0.4669)	(-0.9797)
Precipitation Headquarter$(t-3)$	0.0010	0.0011	0.0010	0.0008	0.0009	0.0008
	(1.5807)	(1.5778)	(1.5206)	(1.7475)	(1.7088)	(1.6280)
Precipitation Exchange × Different				0.0003	0.0003	0.0002
				(0.6997)	(0.6349)	(0.4049)
Precipitation Exchange × Different$(t-3)$				0.0038	0.0037	0.0036
				(1.3123)	(1.2691)	(1.2135)
VIX	9.02e-06	6.672e-07	-9.589e-07	2.954e-06	-8.055e-06	-9.932e-06
	(0.2879)	(0.0229)	(-0.0323)	(0.0936)	(-0.2747)	(-0.3209)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0023	0.0010	0.0016	0.0088	0.0064	0.0066
No. observations	1909202	1909202	1909202	1909202	1909202	1909202
No. firms	17749	17749	17749	17749	17749	17749

Table A2 reports the impact of one-quarter lagged temperature anomaly measurements on the monthly standard deviation of US public firms' daily stock return. The dependent variable is standard deviation. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. In each equation shown in columns, There are also interaction terms for those firms that their exchanges are in different city than their headquarters. $t-statistics$, reported below coefficient estimates in parentheses, are calculated using double clustered standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

Table A3: Accounting for adaptation - Return

	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Headquarter	0.0003					
	(0.7222)					
× Warmer	-0.0004					
	(-0.8709)					
Max Headquarter		-9.836e-05				
		(-0.3584)				
× Warmer		6.064e-05				
		(0.2512)				
Min Headquarter			-0.0005			
			(-1.5880)			
× Warmer			0.0003			
			(1.2329)			
Mean Exchange				0.0010		
				(1.1658)		
× Warmer				1.52e-05		
				(0.0643)		
Max Exchange					0.0003	
					(0.4632)	
× Warmer					-0.0001	
					(-0.6665)	
Min Exchange						-0.0001
						(-0.1693)
× Warmer						1.668e-05
						(0.0971)
Precipitation Headquarter	-0.0001	-0.0002	-0.0003			
	(-0.2980)	(-0.4517)	(-0.8036)			
× Warmer	-0.0003	-0.0002	-8.791e-05			
	(-0.5680)	(-0.4483)	(-0.1925)			
Precipitation Exchange				-0.0002	-0.0002	-0.0002
				(-0.2241)	(-0.2280)	(-0.2411)
× Warmer				-8.419e-05	-9.133e-05	-9.228e-05
				(-0.2793)	(-0.3056)	(-0.3099)
SP500	0.0096	0.0096	0.0096	0.0095	0.0096	0.0096
	(17.768)	(17.856)	(17.784)	(17.350)	(17.570)	(17.664)
× Warmer	7.921e-05	6.529e-05	7.663e-05	6.510e-05	6.857e-05	6.744e-05
	(0.5245)	(0.4380)	(0.5118)	(0.4354)	(0.4602)	(0.4522)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0283	0.0283	0.0283	0.0283	0.0283	0.0282
No. observations	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043

Table A3 reports the impact of different temperature anomaly measurements on warmer locations. These locations are those locations with 100-year average temperature above the median of all historical temperatures in US cities. The dependent variable is log return. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. In each equation shown in columns, there is also an interaction term between these measures and the warmer locations dummy. $t - statistics$, reported below coefficient estimates in parentheses, are calculated using double clustered standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

Table A4: Accounting for adaptation - Standard Deviation

	Standard deviation					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Headquarter	0.0015					
	(1.4038)					
× Warmer	0.0003					
	(1.1966)					
Max Headquarter		0.0003				
		(0.8724)				
× Warmer		0.0003				
		(1.3774)				
Min Headquarter			-0.0011**			
			(-1.9769)			
× Warmer			-3.467e-05			
			(-0.1897)			
Mean Exchange				0.0032*		
				(1.6953)		
× Warmer				1.52e-05		
				(0.0643)		
Max Exchange					0.0014	
					(1.5776)	
× Warmer					-4.137e-05	
					(-0.7264)	
Min Exchange						-0.0021*
						(-1.8182)
× Warmer						4.083e-05
						(0.4282)
Precipitation Headquarter	0.0006	0.0004	1.731e-05			
	(1.0148)	(0.7780)	(0.0443)			
× Warmer	-0.0005	-0.0003	-0.0002			
	(-0.6966)	(-0.4581)	(-0.3091)			
Precipitation Exchange				-0.0003	-0.0003	-0.0005
				(-0.4250)	(-0.4338)	(-0.7566)
× Warmer				-4.909e-06	-2.817e-05	-3.073e-05
				(-0.0563)	(-0.3428)	(-0.3615)
VIX	-7.899e-07	-1.286e-05	-1.2e-05	6.887e-06	-1.132e-05	-2.234e-05
	(-0.0217)	(-0.3837)	(-0.3537)	(0.1800)	(-0.3232)	(-0.5875)
× Warmer	-6.159e-06	-4.797e-06	-9.572e-06	-4.535e-06	-4.3e-06	-4.669e-06
	(-0.9849)	(-0.9500)	(-1.4974)	(-0.9843)	(-0.9598)	(-0.9945)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0019	0.0004	0.0020	0.0048	0.0022	0.0041
No. observations	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043

Table A4 reports the impact of different temperature anomaly measurements on firms' standard deviations located in warmer locations. These locations are those locations with 100-year average temperature above the median of all historical temperatures in US cities. The dependent variable is the monthly standard deviation. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. In each equation shown in columns, there is also an interaction term between these measures and the warmer locations dummy. $t-statistics$, reported below coefficient estimates in parentheses, are calculated using double clustered standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

Table A5: Effect of temperature anomaly on Return (Quarter-Industry FE)

	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Headquarter	0.0002			-7.792e-05		
	(0.6689)			(-0.3145)		
Max Headquarter		3.108e-05			-4.803e-05	
		(0.1453)			(-0.2916)	
Min Headquarter			-0.0005**			-0.0004*
			(-2.3462)			(-1.8781)
Mean Exchange × Different				0.0015		
				(1.6111)		
Max Exchange × Different					0.0003	
					(0.6037)	
Min Exchange × Different						-0.0007
						(-1.1555)
Precipitation Headquarter	-6.607e-06	-1.616e-05	-0.0001	-6.118e-05	-4.744e-05	-0.0001
	(-0.0324)	(-0.0784)	(-0.5889)	(-0.3249	(-0.2529)	(-0.6486)
Precipitation Exchange × Different				8.28e-05	0.0001	-1.328e-05
				(0.0940)	(0.1512)	(-0.0151)
SP500	0.0088	0.0088	0.0088	0.0087	0.0088	0.0088
	(17.407)	(17.427)	(17.469)	(17.371)	(17.495)	(17.342)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0171	0.0171	0.0171	0.0172	0.0171	0.0172
No. observations	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043

Table A5 reports the impact of different temperature anomaly measurements on US firms' return Using **Quarter-Industry** fixed effect. The dependent variable is log return. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. There are also interaction terms for those firms that their exchanges are in different city than their headquarters. $t - statistics$, reported below coefficient estimates in parentheses, are calculated using double clustered standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).

Table A6: Effect of temperature anomaly on Standard Deviation (Quarter-Industry FE)

	Standard deviation					
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Headquarter	0.0011			0.0005		
	(1.4515)			(1.1267)		
Max Headquarter		0.0003			-1.498e-07	
		(0.9323)			(-0.0006)	
Min Headquarter			-0.0008**			-0.0003
			(-2.0117)			(-1.3135)
Mean Exchange × Different				0.0030*		
				(1.9322)		
Max Exchange × Different					0.0016*	
					(1.8600)	
Min Exchange × Different						-0.0022**
						(-2.0772)
Precipitation Headquarter	0.0002	0.0002	2.279e-06	0.0001	6.441e-05	-2.459e-06
	(1.4018)	(1.2405)	(0.0156)	(0.8872)	(0.5368)	(-0.0183)
Precipitation Exchange × Different				-0.0003	-0.0003	-0.0006
				(-0.4162)	(-0.3567)	(-0.7471)
VIX	-2.053e-05	-2.731e-05	-2.813e-05	-9.374e-06	-2.506e-05	-3.23e-05
	(-0.5623)	(-0.7899)	(-0.8246)	(-0.2364)	(-0.7082)	(-0.8956)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0008	0.0003	0.0009	0.0035	0.0019	0.0036
No. observations	1963007	1963007	1963007	1963007	1963007	1963007
No. firms	18043	18043	18043	18043	18043	18043

Table A6 reports the impact of different temperature anomaly measurements on US firms' stock return standard deviation Using **Quarter-Industry** fixed effect. The dependent variable is Standard deviation. There are several measurements available for independent variables, including monthly mean temperature deviation, monthly maximum temperature deviation, and monthly minimum temperature deviation, all calculated from the 30-year moving average of each specific month. There are also interaction terms for those firms that their exchanges are in different city than their headquarters. $t - statistics$, reported below coefficient estimates in parentheses, are calculated using double clustered standard errors for both firms and time. Significant results are specified by * (P-value < 0.10), ** (P-value < 0.05) and *** (P-value < 0.01).