Volatile Temperatures and their Effects on Equity Returns and Firm Performance*

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Abstract

We present a statistic to generally represent the variability of temperature anomalies and demonstrate its consequences on US firms and investors. We develop a spatial hedging strategy to account for differentially exposed firms, resulting in a large market-adjusted alpha for the least vulnerable firms. Cross-sectional asset pricing tests show that the metric is also a significant factor in the cross-section of equity returns for specific industries. We investigate whether the price reaction to our temperature measure results from firm operations or investor attention and find evidence for both. In each step of our exercise, we contrast our measure with average temperature anomalies and demonstrate that our metric is the first-order feature. Our statistical framework is scalable and can serve as a reference to assess the quantitative effects of physical climate risks for other geographies.

Keywords: Temperature variability, Stock Returns, Climate Attention, Firm Performance, Corporate Climate Reporting.

JEL classification codes: C21; C23; G12; G32; Q54.

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1 Introduction

Global changes in the climate are resulting in substantial deviations of temperature from its historical norm, commonly known as a temperature anomaly. Climate science has determined two key facts regarding the *distribution* of temperature anomalies: that both the mean and variability have increased as illustrated in Figure 1. Much of the prior discussion centers on understanding the financial repercussions of the first fact, geographically identifying deviations of observed temperatures from the historical averages (mean temperature) and evaluating their effects on asset prices (e.g., Schlenker and Taylor (2021), Acharya et al. (2022), Pankratz et al. (2023), Addoum et al. (2021)). Although studies by Choi et al. (2020) and Kruttli et al. (2021) suggest that fluctuations in average temperature have an impact on investor attention and expectations, it is unclear whether these effects translate into significant changes in firm performance, as evidenced by the less conclusive findings reported by Addoum et al. (2020).

Running concurrent to this debate is the push from various government agencies such as the Securities and Exchange Commission (SEC) and the European Financial Reporting Advisory Group (EFRAG) that have been advocating for greater transparency from companies regarding the disclosure of *material* physical climate risks. However, the materiality of such risks remains unclear for many firms, prompting agencies like the European Central Bank (ECB) and the International Financial Reporting Standards (IFRS) Foundation with the International Sustainability Standards Board (ISSB) initiative, to release sets of statistical indicators aimed at improving the assessment of climate-related risks by financial actors.[1] Our investigation, motivated by these needs, studies the evolving distribution of temperature anomalies and their impact on asset prices. We find that shocks to the variability of temperature anomalies, rather than to the mean, change investor attention and expectations, and materially influence firm performance.[2]

The key innovation in this paper is the development of two replicable metrics, TA and TAV, that capture shocks to the mean and standard deviation of temperature anomalies, respectively. We observe that equity returns largely do not respond to deviation in the mean of temperature anomalies, but rather to changes in the variability. At the industry level, we find that the utility, energy, consumer discretionary, and consumer staples sectors are the most impacted. We attribute these return deviations to three primary factors: an investor attention channel, a reduction in cash flow expectations, and a rise in cost of capital expectations. The changes in expectations are justified as exposure to TAV affects operating performance heterogeneously across industries. Lastly, we propose a methodology that firms can use to disclose their future exposure according to climate projections, offering practical guidance for policymakers.

The essence of the paper focuses on isolating the differential exposure of U.S.-based firms to the two temperature shocks. To accomplish this, we formulate our metrics using the maximum surface temperature data at a 1 by 1 degree grid level, sourced from Berkeley Earth (BEST) (Rohde and Hausfather, 2020). We aggregate this data to calculate exposure

[1]ISSB standards – IFRS S1 and IFRS S2 – available "IFRS Sustainability Disclosure Standards", 2023. ECB guidance is available "Towards climate-related statistical indicators", 2023.

[2]Donadelli et al. (2019) and Kotz et al. (2021) studying changes in variability; however, they primarily focus on macro-economic outcomes.

at the state level, as illustrated in Figure 2, which highlights the distinct spatial variation of the two metrics.[3] This setting enables us to test the differences between the two arguably exogenous temperature shocks (see (Auffhammer et al., 2013); (Dell et al., 2014); (Pankratz et al., 2023)) and their effects across time and space on firms that are part of Russell 3000. The headquarters of these firms are matched to TA and TAV under the assumption that the primary locus of operational activity is centered in that state. However, for geographically dispersed firms, we employ a state count methodology as outlined in Garcia and Norli (2012).

It is unclear ex-ante which representation of changes in the distribution of temperatures should affect asset prices. Under standard asset pricing assumptions, the regional and idiosyncratic nature of temperature shocks should not be priced. However, recent evidence from Kruttli et al. (2021) suggests that idiosyncratic hurricane shocks are indeed priced and affect discount rates and cash flows, as predicted under the model of Merton et al. (1987). Although using fundamentally different measurements of temperature exposure, Pankratz et al. (2019) and Addoum et al. (2021) find a similar decrease in cashflows of firms affected by extreme temperatures. In line with this theory, we hypothesize that the idiosyncratic and exogenous shocks of TA and TAV should affect the returns of exposed firms.

We begin by implementing a geographic long-short portfolio strategy using the Russell 3000 firms to study the return effect caused by state-level exposure to each temperature metric. A monthly strategy that goes long firms headquartered in states that are least affected by TAV and short those most affected, produces an average value-weighted return of 4.47% per year for the least exposed quartile when controlling for common factors. In contrast, the strategy using TA yields insignificant factor-adjusted returns of 2.16% per year for firms located in the least impacted states. The results become more pronounced when narrowing the sample to industries like energy and utilities, as well as the consumer discretionary and consumer staples sectors, especially when leveraging variation in TAV over TA. These results underscore our primary contribution, equities react to changes in the variability of temperature anomalies rather than to the average – a consistent finding throughout the paper.

To gain a detailed understanding the impact of temperature anomalies on industry-specific returns, we conduct monthly cross-sectional regressions that control for firm characteristics. Our results reveal substantial heterogeneity across sectors, with negative relationships between shifts in temperature variability and returns observed for the energy, consumer staples, and consumer discretionary segments. However, we find positive and significant coefficients for TAV in the energy, utilities, consumer staples, and consumer discretionary sectors. The energy and utility sectors are once again affected by temperature variability, which reinforces the validity of our exercises. Shocks to monthly temperature anomalies, on the other hand, are only economically consequential for the utilities sector. We also find that our return patterns hold across various sub-periods, suggesting that the return response is continual and that adaptation is either lacking or neglected.

The overarching results suggest that TAV is a salient physical risk for a large set of sectors. However, these empirical results prompt the question of whether the observed return reaction stems from heightened investor attention and a shift in climate beliefs or from actual

[3]While our focus is at the US state level, the metrics can be calculated for any region and various periodicities such as quarterly or yearly.

operational impacts. The clarity on investor attentiveness to climate shocks remains elusive. For instance, Hong et al. (2020) reports inattention to droughts, while Choi et al. (2020) finds the opposite for heatwaves.[4] We endeavor to disentangle the two mechanisms by conducting a series of exercises that extract evidence aligning with both perspectives.

A behavioral rationale for the observed return reaction posits that investors' attention is a limited resource (Van Nieuwerburgh and Veldkamp, 2010). This attention can be redirected when unusual weather events occur, subsequently altering the equilibrium price of an asset. However, given the regional nature of weather, temperature shocks would likely impact only a select group individuals, making such shocks idiosyncratic and resulting in minimal price impact (Alekseev et al., 2021). Contrary to this prevailing notion, our results align with Kruttli et al. (2021), indicating that deviations in the variability of temperature anomalies are linked to both localized and broader market attention to climate change risks, rather than shifts in the average of temperature anomalies. Our interpretation is that, despite the regional nature of the temperature anomaly shock, local attention is relayed to news agencies like the Wall Street Journal and then disseminated to the broader investment community, influencing prices.

To explore the attention channel at both the state and U.S. national levels, we aggregate the temperature metrics accordingly. After obtaining the innovations of Google Search Volume Index (SVI) data at the state level for the topics "Climate Change" and "Temperature", we determine whether investors react to localized temperature shocks. In doing so, we identify a strongly significant relationship between TAV and both SVI topics, lending credence to the attention mechanism. Utilizing the *The Wall Street Journal* (WSJ) news index from Engle et al. (2020), which gauges overall U.S. media coverage of climate change tailored for investors, we find a moderate relationship between TAV and unexpected news in the index, but none for TA. Collectively, these results bolster the notion of a behavioral mechanism where both local and broader investors adjust their perceptions regarding the impacts of physical climate risks.

Next, to further validate the attention channel, we examine whether sell-side analysts probe firms that experience temperature shocks during earnings calls to further verify the attention channel. We utilize a measure of earnings call attention to physical risk developed by Sautner et al. (2020) and relate it to our temperature metrics. We find a positive correlation with all firms, especially in the utilities industry. However, their measure is swayed by broader attention to climate change, as evidenced by its positive relationship with the WSJ index. After controlling for the index, we observe that only elevated TAV is significantly and positively associated with an unexpected surge in attention paid by analysts to affected firms. These results underscore the significance of TAV for investors, suggesting that temperature shocks act as a "wake-up call," prompting a shift in prices through the behavioral attention channel.

We subsequently delve into the impact of changes in the distribution of temperature anomalies on the financial performance of firms. In line with Brown et al. (2021), we measure the annual performance of firms using their operating income and sales, normalized by their assets, and regress these on a set of conventional firm controls and the time series of both

[4] Prior work to affect beliefs about aggregate climate risk (see, e.g., Egan & Mullin 2012, Deryugina 2013, Joireman et al. 2010, Li et al. 2011, Fownes & Allred 2019, Sisco et al. 2017)

temperature metrics. Our analysis reveals a negative correlation between TAV and cash flows for industry, consumer, and energy sectors, with utilities showing non-significant positive cash flows. A one standard-deviation surge in yearly TAV diminishes their return on assets by 1.37% of total assets across the entire sample. This effect is more pronounced for the consumer discretionary and consumer staples sectors, where the impact reaches 3.35% of assets. On closer inspection, we observe smaller effect sizes when examining the relationship between TAV and sales. This suggests that heightened variability adversely influences both sales and operating expenses for most firms.

Our findings carry practical implications for policymakers and firm managers, especially in light of the mounting global emphasis on climate risk disclosure. The increasing awareness of climate change and its potential impacts on businesses has necessitated the development of robust metrics. In this context, organizations like the International Sustainability Standards Board (ISSB) and the European Financial Reporting Advisory Group (EFRAG) have been actively pursuing the development of metrics that encapsulate financial materiality. Their goal is to pinpoint the most appropriate methods for qualifying and quantifying the financial repercussions of climate risks. We illustrate the practical utility of TAV through examples of measuring and reporting temperature risks. In the first exercise, we illustrate how companies can leverage TAV to disclose their exposure to temperature risks. Such disclosures not only enhance transparency but also inform financial markets and investors about the company's vulnerability to climate-induced temperature shocks. In the second exercise, we demonstrate how TAV can act as a barometer to gauge the potential risks associated with an investor's portfolio. By evaluating the TAV of companies within their portfolio, investors can make informed decisions, adjusting their portfolio away from firms negatively impacted by temperature anomalies.

Lastly, we conduct a battery of robustness checks and extensions to validate our results. We affirm the exogeneity of the temperature metrics using a spatio-temporal transition matrix. Moreover, we establish that TAv, rather than TA, predominantly influences the prices of weather derivatives from the Chicago Mercantile Exchange (CME) weather futures market. We also determine that energy consumption reacts more to deviations in the variability of temperature anomalies. We do this by associating it with unexpected state-level energy demand in the US. The analysis yields positive significant coefficients for TAV on aggregate energy demand, particularly in the residential and industrial sectors. Conversely, shifts in temperature anomalies yield a significant positive coefficient only for the commercial sector, which can be attributed to the sector's consistent and steady energy demand. The collective evidence compellingly indicates that fluctuations in temperature variability from its historical average is a first-order factor in the closely linked energy and weather futures market.

Our study contributes to four main strands of the climate change financial literature: (i) constructing salient physical climate risk measures (ii) identifying equity reactions to climate shocks (iii) attributing them to an attention and investor expectation channel (iv) and estimating financial damages from climate hazards. The TAV metric characterizes a distinctive phenomenon of changes in the *variability* of temperature anomalies occurring due to increasing global green house gas emissions. The generality of TAV means that we are able to treat cold spells as equally harmful to economic activity as heatwaves. The majority of research focus on heatwaves or defining abnormal temperatures as temperature extremes, i.e., temperatures being above or below certain thresholds. For example, Addoum et al.

(2020) construct exposure measures based on the idea of days exceeding a certain threshold, e.g., above or below a predetermined percentile. Their findings suggest mostly insignificant of abnormally high or low temperatures on firm sales with the exception of a positive impact of low temperature on sales in the energy sector.

We also contribute to the literature by examining stock return reactions to climate shocks. We build upon the temperature volatility study of Donadelli et al. (2017) in a concrete manner: first, by developing a long–short strategy to explore investor reactions to sub-national heterogeneity in temperature in the U.S. equity market. second, performing an asset pricing factor analysis to examine the relationship between deviations in temperature variability and U.S. stock returns; and third, directly validating the importance of deviations in temperature variability in the energy consumption and weather futures market.

We add to existing body of research is the investigation of the impact of temperature extremes on investor reactions and attention. Engle et al. (2020) builds the WSJ climate news series to hedge against long-term climate risks. Choi et al. (2020) finds that local temperature shocks can heighten investors' attention, which in turn differentially affects returns on a cross-section of stocks. Alekseev et al. (2021), with a similar argument, investigates the effects of local temperature shocks, finding that mutual funds respond by shifting their portfolio allocation, irrespective to the intensity of the heat shocks. We complement the majority of these findings, similarly concluding that investors do react to temperature swings. Specifically, deviations in temperature variability lead either to direct attention to a local shock, as in Choi et al. (2020) and Alekseev et al. (2021), or to indirect investor attention to increased news coverage distributed more broadly. Critically, however, we discover that the pricing reaction only occurs in response to a specific type of temperature shock. Furthermore, we go a step further by disentangling attention from firm-level exposure to the risk.

Last but not least, our study contributes to the literature by identifying temperature shocks and their impact on firm performance. Hong et al. (2020) investigates its effects on the international food industry, Pankratz and Schiller (2021) and Addoum et al. (2021) firm earnings and profits, and Schlenker and Taylor (2021) studies incorporation of temperature into futures markets.

This paper is organized as follows. Section 2 details the data sourcesa nd explains our data set construction procedure. In section 3, we describe the construction of the temperature statistics TA and TAV. Section 4 delves into the influence of shocks in temperature on equity returns. Section 5 differentiates the impact of TAV on investor attention Section 6 pinpoints the direct effects of TAV and TA on firms. The last section illustrates the practical utility of TAV through examples of measuring and reporting temperature risks. Section 9 concludes.

2 Data construction

2.1 Data sources

Our sample is constructed by merging data from several databases. We use the Berkeley Earth Surface Temperatures to collect a gridded reconstruction of daily land surface air temperature records. In addition, we extract daily maximum and minimum temperatures from over 25,000 stations using the U.S. National Oceanic and Atmosphere Administration

(NOAA) repository. For financial data, we turn to the Center for Research in Security Prices (CRSP) files to gather stock returns and the Standard and Poor's Compustat database for financial information. We leverage Google Trends to collect data on the Google Search Volume Index (SVI), which aids us in identifying days of heightened national and regional interest in climate change and temperature-related topics. We cross-reference the Google SVI data with the climate change news risk index from Engle et al. (2020) to distinguish climate-related events that garnered attention from U.S. news outlets or were featured in major newswires. Lastly, we use the Federal Reserve Economic Database, released by the Federal Reserve Bank of St. Louis, to obtain data on population and gross domestic product.

2.2 Temperature

We obtain daily temperature data from the Berkeley Earth Surface Temperatures (BEST), which are produced by Berkeley Earth. We consider data starting from Jan 1, 1950 and ending on Dec 31, 2019. The BEST data are organized into a grid format, with each grid cell representing a 1-degree latitude by 1-degree longitude area. One of the key strengths of the BEST data set is its use of a large number of land stations. With data from over 40,000 stations, BEST significantly surpasses alternative data sets, which typically use around 10,000 stations. This extensive network of stations enhances the accuracy of the BEST data set, particularly when it comes to identifying record-setting daily temperatures.[5] BEST utilizes a spatial interpolation technique to ensure comprehensive and extensive spatial coverage globally, from 1950 to the present day. This means that the dataset provides a continuous and detailed record of temperature changes over several decades,[6] covering the entire globe. This is of paramount importance when examining the impact of temperature on businesses operating in different countries. While the primary focus of this paper's analysis is on the United States, the methodologies and metrics used can be applied to other countries or adjusted to different geographic scales. The flexibility of the BEST dataset, with its comprehensive global coverage and detailed temperature records, allows for such adaptability and, crucially, consistent comparability of the effect of temperature across different countries. This consistency aligns seamlessly with the objectives of the International Sustainability Standards Board (ISSB), which seeks standardized and comparable sustainability reporting across jurisdictions. Leveraging the BEST dataset can thus aid firms in meeting the rigorous and harmonized reporting standards advocated by the ISSB, ensuring that temperature-related disclosures are both accurate and universally interpretable.

In our base formulation, we attribute equal weight to each grid within the state borders when assembling state-level temperature data. However, we recognize that the significance of temperature exposure in each state can differ based on the economic activities occurring in that particular state. Therefore, to assemble U.S.-level temperature data starting from state-

[5] In other words, the more stations contributing data, the more accurate the assessment of whether a given day's temperature was record-setting. This is because a larger number of stations increases the likelihood that the data set includes a station near the location of interest, reducing the need for interpolation between distant stations and thus improving the accuracy of the data.

[6] Such a technique is crucial for accurately tracking the progression of temperature extremes over the past hundred years. For a more technical exploration of this topic, we direct readers to Rohde et al. (2013) and Rohde and Hausfather (2020).

level data we consider state-level economies and, for robustness, populations when assigning weights to temperature values. The rationale for this approach is that these elements act as proxies for a state's exposure to temperature, as discussed in CIT. Specifically, we use annual data on the economies and populations of U.S. states, sourced from the Federal Reserve Economic Database, released by the Federal Reserve Bank of St. Louis. State-level population data can be retrieved using the 'POP' code, which delivers annual population values from 1950 onwards. To align with the temperature datasets, we interpolate the annual frequency of the population data to produce monthly or daily series. Data on Gross Domestic Product (GDP) can be accessed using the 'RQGSP' code, which yields quarterly real gross product data for each state. We implement a similar interpolation technique to this data to generate a monthly or daily series.

2.3 Stock and company information

We gather stock returns for the Russell 3000, an index that monitors the performance of the 3,000 largest U.S. companies, which collectively represent about 97% of the U.S. equity market that's available for investment. Information on the financial and accounting performance of the constituents of the Russell 3000, along with their headquarter locations, are sourced from Refinitiv – Thomson Reuters. Furthermore, these companies are categorized into their respective sectors using the Global Industry Classification Standard (GICS). Table 1 presents summary statistics of various financial parameters, including capitalization, book-to-market ratio, return on equity, leverage, capital expenditure, and the value of long-term assets.

2.4 Firm geographic concentration

One difficulty in capturing the effects of temperature on firms is that their headquarters may not represent the firm's center of operations. To adjust our strategy for firm level geographic dispersion, we use the methodology outlined in Garcia and Norli (2012) and Bernile et al. (2015) who develop a 10-K-based measure of firm local exposure. We parse the 10-K filings of all Russell-3000 firms for each year to identify the number of times the U.S. states and Washington DC are mentioned in sections 1A, 2, 6, and 7. The firm-headquarter citation count is calculated by dividing the total number of mentions of the headquartered state by the total mentions of all U.S. states and Washington DC. Finally, we average this for each firm to obtain a metric which we define as the 10-K measure of state operational dispersion. Akin to Bernile et al. (2015), we assert that our metric is a reasonable proxy to capture geographical variation in firm's activities.

Figure 5 shows the distribution of operational dispersion with values closer to one meaning that firm activity is in the home state. The dispersion metric is right skewed, showing that the majority of firm activity in the Russel-3000 is scattered in states other than their headquarters. While the prior literature provides no theoretical motive for a cutoff for the metric, we remove the bottom quartile of firms using the operational dispersion (14.13%) which leaves 2,500 firms remaining in the sample. This limit reduces the number of firms that are least geographically concentrated in the U.S.

An additional issue is that the number of firm headquarters is unevenly and heterogenously distributed across states. Since our long-short strategy hinges on sorting states based on their exposure to temperature, states with minimal headquartered firms could skew the 'alpha' values in the portfolio. Therefore, we remove 10 states with the fewest headquartered firms: Alaska, Hawaii, Maine, Montana, New Mexico, Rhode Island, North Dakota, Vermont, South Dakota, and West Virginia. Each of these states have fewer than 14 firms headquartered in their state. Together with the operational dispersion adjustment, there are 2400 firms in our sample.

2.5 Other data

Attention indices We draw from three different data sources that measure market attention to climate risks for our empirical tests. We begin by extracting internet search activity data from Google Trends, which offers a Search Volume Index (SVI) for the search topics "climate change" and "climate variability and change." We download the quarterly SVI for each of the 50 U.S. states from 2004 (the inception of Google Trends) through to 2021.

To represent firm-specific attention paid by analysts, we adopt the physical climate change exposure index developed by Sautner et al. (2023). Their measure captures the proportion of bigrams related to physical climate change (e.g., "natural hazard" and "global warm") that occur out of all bigrams in the transcripts of earnings conference calls. We obtain the yearly frequency of their measure from 2005 to 2019 and match it to the Russell 3000 firms in our sample.

Additionally, we use the Wall Street Journal climate change news index from Engle et al. (2020) to proxy for US market-wide investor attention to the physical and transition risks related to climate change. The series is based on the assumption that any news about climate change is bad news. The news index is broken down by month, covering July 2008 through June 2017. When using this index, our sample is truncated to reflect this shortened time period.

Energy demand We gather data spanning from September 1990 to December 2020 on energy consumption. We source time-series data on energy demand for all 50 U.S. states at a monthly frequency from the U.S. Energy Information Administration. In the U.S., energy consumption is classified into four end-use sectors. These include residential (homes and apartments), commercial (offices, malls, stores, schools, hospitals, hotels, warehouses, and public assembly), industrial (facilities and equipment used for manufacturing, agriculture, mining, and construction), and transport. By analyzing energy consumption data across these sectors, we can understand how temperature impacts energy demand in different areas of the economy.

Weather derivatives We obtain daily futures prices (end of day) for temperature derivatives traded on the Chicago Mercantile Exchange (CME) from Bloomberg, covering the period from 2005 to 2020. These contracts provide insurance to buyers against extreme heat or cold during a specified time period. The two primary temperature instruments are Heating Degree Day (HDD) contracts and Cooling Degree Day (CDD) contracts.[7] These contracts

[7]An HDD contract buyer receives payments for cold days, defined as days when the average temperature falls below 65°F. On the other hand, a CDD contract buyer receives payments for hot days, defined as days

are available for eight geographically diverse cities across the U.S. and are based on the observed temperature at a specific weather station near the contract city for a particular period. The cities we've selected for our study, as considered in Diebold and Rudebusch (2019) and Schlenker and Taylor (2021), are Atlanta (ATL), Chicago (ORD), Cincinnati (CVG), Dallas Fort Worth (DFW), Las Vegas (LAS), Minneapolis St Paul (MSP), New York (LGA), and Portland (PDX). Table 13 indicates which of the cities in our larger city sample have temperature derivatives available.

Consumer transactions To measure consumer spending in various geographic areas in the US, we acquire SpendTrend data from Bloomberg. The data captures total retail monthly transactions in nine major metropolitan statistical areas from May 2016 to December 2019. The nine metropolitan areas include: Washington, Atlanta, Greater Boston, Chicago, Dallas-Fort Worth, Greater Houston, Greater Los Angeles, San Francisco, Miami, New York, and Philadelphia-Camden-Wilmington. We average our temperature metrics across various states to match the metropolitan retail data for Washington and Chicago. Specifically, we average temperatures for Virginia and Maryland to correspond to the Washington metropolitan area. For the Chicago metropolitan area, we average the temperature metrics across Illinois and Indiana.

3 Temperature variability

Temperature has a significant impact on economic activities at the macro level, as evidenced by numerous studies (Dell et al. (2012), Burke et al. (2015), Kalkuhl and Wenz (2020)). These effects are not limited to any single sector but span across various aspects of the economy and society. Empirical research has demonstrated the influence of temperature anomalies, i.e. deviations of observed temperatures from the historical averages, on a wide array of observable outcomes (Carleton and Hsiang (2016)). For example, unusually hot and unusually cold temperatures can have a significant impact on agricultural productivity (Schlenker et al. (2006), Wheeler et al. (2000), and Ceglar et al. (2016)). Temperature anomalies, particularly those resulting in unusually high temperatures, can lead to a decrease in individual productivity, especially in tasks that expose workers to heat (Cachon et al. (2012) and Somanathan et al. (2021)). Extreme temperature events, whether excessively hot or cold, can lead to health complications such as heat stroke. These health issues can subsequently result in a decrease in the number of hours worked and a reduction in the time spent on outdoor leisure activities (Graff Zivin and Neidell (2014), Behrer and Park, 2019). Moreover, these extreme temperatures can have serious implications for human health and can even increase mortality rates (Deschenes and Greenstone, 2011, Zanobetti et al., 2011). In the financial literature, empirical research has examined the effects of extreme temperatures on firm performance outcomes and stock valuations. Studies suggest that heightened exposure to extreme temperatures tends to diminish firms' revenues and operating income (Pankratz et al. (2023)). However, it appears that productivity growth (Addoum et al. (2020)) remains largely unaffected, and both analysts and investors typically do not react significantly to extreme temperature events (Addoum et al. 2021).

when the average temperature rises above 65°F.

The ultimate influence of temperature on economic activities and financial results hinges on the effects of those temperature anomalies that become comparatively more (or less) frequent as a result of temperature variability.[8] Essentially, it's the change in the distribution of these temperature anomalies, and ultimately the likelihood of temperature extremes, rather than the average temperature anomaly itself, that matters. In fact, there is already evidence that variability of daily temperature from seasonal and historical expectations has significant impacts on crop yields (Mendelsohn et al. (2007)), human health (Hovdahl (2020)), sales and operational costs (Bertrand and Parnaudeau (2015)), consumer spending (Starr (2000)), and investor expectations (Makridis and Schloetzer (2021)). Temperature variability can have profound effects on businesses too. Firms operating in sectors sensitive to temperature may see their operational efficiency and profitability directly affected by temperature variability. For instance, more frequent warm or cold temperatures can disrupt production schedules, increase operational costs, and affect the demand for products and services. These operational disruptions and increase operational costs can, in turn, impact firm performance outcomes, leading to fluctuations in stock values as investors adjust their expectations based on the firm's ability to manage these climate-related risks. In this study, we explore the relationship between temperature anomalies, the variability in temperature anomalies, and investors' reactions as reflected in stock prices. We aim to understand how these temperature-related factors can materially affect a firm's performance and, consequently, influence investor sentiment and decision-making.

3.1 Temperature anomaly and temperature anomaly variability

Inspired by Kotz et al. (2021) and Linsenmeier (2022), we define day-to-day temperature anomalies for a given location as deviations of the observed temperature from its historical average. Our approach to constructing the temperature anomaly measure subtly but significantly diverges from the one used in Kotz et al. (2021) and Linsenmeier (2022). Our version captures not only the inherent, contemporaneous variability but also some aspects of the underlying warming trend.[9] However, we account for the warming trend in a subsequent step. Formally, we first calculate

$$TA_{s,[d,m,y]} = (T_{s,[d,m,y]} - \overline{T}^{1960-2005}_{s,[d,m]}). \tag{1}$$

In the given formula, $TA_{s,[d,m,y]}$ represents our measure of day-to-day temperature anomaly on a specific day d, month m, year y and location s, calculated from the observed maximum temperature $T_{s,[d,m,y]}$. The term $\overline{T}^{1960-2005}_{s,[d,m]}$ denotes the historical average temperature at the same location s and on the same day d and month m, over the period 1960–2005.[10] This

[8] While temperature extremes are indeed anomalies, not all temperature anomalies qualify as extremes. An anomaly can occur when a temperature is only slightly higher or lower than the average, but it won't be deemed an extreme unless it ranks among the very hottest or coldest temperatures ever recorded. Crucially, an increase in the frequency and intensity of temperature anomalies can shift the range of temperatures we experience, which in turn leads to more frequent occurrences of temperature extremes.

[9] It's important to note that while Kotz et al. (2021) and Linsenmeier (2022) focus on the variability of temperature, our emphasis is on the variability temperature anomalies.

[10] While $\overline{T}^{1960-2005}_{s,[d,m]}$ is a constant over the year, and does not affect the time series, it does however vary across location s and will affect the cross-sectional properties of $TA_{s,[d,m,y]}$.

historical average is calculated using a smoothing window of 5 days around day d. Thus the historical average daily temperature is calculated as the average of the temperatures on a specific day, as well as the two days before and the two days after. This approach helps to smooth out any short-term fluctuations in temperature and provides a more stable estimate of the typical temperature for that day and location.

To compare temperature variables with financial data, an assessment must be made at the monthly level. The location-specific temperature anomaly is therefore averaged across the days of a given month to yield a monthly measure of day-to-day temperature anomaly:

$$TA_{s,[m,y]} = \frac{1}{D_{[m,y]}} \sum_{d=1}^{D_{[m,y]}} TA_{s,[d,m,y]}, \tag{2}$$

where $D_{[m,y]}$ is the number of days in month m of year y. For convenience, we will henceforth relabel $TA := TA_{s,[m,y]}$.

In line with Katz and Brown (1992) and Donadelli et al. (2020), we examine changes in the distribution of temperature anomalies by focusing on shifts in their variability. Specifically, we track changes in the dispersion of temperature anomalies over time. This approach allows us to capture changes in the likelihood of extreme temperature events. In the context of climate change risk reporting, understanding these fluctuations is of paramount importance as they can signal potential shifts in the frequency and intensity of extreme temperature events. To facilitate this, we employ a Temperature Anomaly Variability Index (TAV), defined as the difference between the intra-month variability of temperature anomalies and a benchmark variability level of temperature anomalies. This benchmark is represented by the historical average intra-month variability of temperature anomalies, calculated over the period from 1960 to 2005. The intra-month variability of temperature anomalies is calculated as follows:

$$\sigma(TA_{s,[m,y]}) = \frac{1}{D_{[m,y]}} \sqrt{\sum_{d=1}^{D_m} (TA_{s,[d,m,y]} - TA_{s,[m,y]})^2}, \tag{3}$$

In this equation, $\sigma(TA_{s,[m,y]})$ represents the standard deviation of the temperature anomalies for a given location s in a specific month m and year y. This value measures the extent to which the temperature anomalies deviate from their average value for that month. Equipped with $\sigma(TA_{s,[m,y]})$, we then calculate the Temperature Anomaly Variability Index:

$$TAV_{s,[m,y]} = \sigma(TA_{s,[m,y]}) - \overline{\sigma}(TA_{s,[m]})^{1960-2005}. \tag{4}$$

TAV represents how much the temperature anomalies variability fluctuates around its historical average. If the variability increases, resulting in a positive TAV, it implies that temperature anomalies are fluctuating more widely than usual, potentially leading to more frequent and intense periods of extreme heat or cold. Conversely, if the variability decreases, yielding a negative TAV suggests that temperature anomalies are more stable and less likely to reach extreme levels.

We now introduce spatial aggregation of the temperature data and illustrate our measures of temperature anomaly and temperature anomaly variability by examining temperature data for two states: New Mexico and Arizona.

Beginning with the grid-level data from BEST, which assigns a temperature field at a 1-degree resolution within U.S. land borders, we calculate a state-aggregated temperature as follows:

$$T_{s,[d,m,y]} = \sum_{i=1}^{N_s} w_i \cdot T_{i,[d,m,y]}, \tag{5}$$

where $T_{i,[d,m,y]}$ represents the maximum temperature for grid cell i on day d, month m, and year y. N_s is the number of grid cells that at least partially fall within state s. w_i is the weight associated with the grid cell. In the following analysis, we assign equal weight to the grid cells by setting the weights w_i equal to $1/N_s$.[11] Essentially, $T_{s,[d,m,y]}$ is an equally weighted average of the temperature assigned to each grid cell in state s. In Appendix B, we discuss alternative aggregation methods. For instance, in the case of aggregation by population, the weight represents the proportion of the population within that grid cell. This spatial aggregation enables us to derive temperature anomaly TA and temperature anomaly variability TAV for each state s in the U.S., as outlined in expressions (1) and (4).

Figure 3 depicts the state-level temperature across the U.S. for September 2015. Panel A presents the state-level temperature anomaly TA, while Panel B showcases the state-level temperature anomaly variability TAV.

To elucidate the distinctions between the measures of temperature anomaly TA and temperature anomaly variability TAV, we examine the monthly TA and TAV for two distinct states, New Mexico and Arizona, in the year 2017, as depicted in Figure 4. The left panel showcases the TA, as computed in expression (1), for the State of New Mexico (blue color) and the State of Arizona (yellow color). The bars illustrate the divergence of the monthly temperature from its historical average for the year 2017, represented by the horizontal line at zero. Bars above the line signify that the temperature exceeded the average, while bars below the line indicate that the temperature fell short of the average. Conversely, the right panel presents the TAV, as computed in expression (4), for the State of New Mexico (blue color) and the State of Arizona (yellow color). Despite both states experiencing comparable levels of temperature anomalies in the year 2017, Arizona is marked by greater variability in temperature anomalies. This implies that temperature anomalies in Arizona are fluctuating more broadly than usual, potentially leading to more frequent and severe periods of extreme heat or cold.

This comparison underscores the possibility of observing more adverse temperature effects in states that experience the same monthly temperature anomaly but exhibit different levels of temperature anomaly variability.

4 Equity returns in response to temperature shocks

4.1 Exposure using a long-short portfolio

In this section, we examine the contemporaneous effect of temperature anomalies $\widetilde{TA}$ and deviations in temperature variability TAV on the equity returns U.S. headquartered firms

[11] Our method of constructing sub-national temperature measures aligns with the approach used in other studies, such as that by Burke and Tanutama (2019).

in the Russell 3000. Our empirical prediction is that temperature shocks will be associated with a collective reaction from investors (Choi et al., 2020) as well as materially affect a firm's performance (Pankratz et al., 2023), leading to negative returns for those firms most affected.

We construct monthly long-short (L/S) portfolios by sorting the exposure of firms' operational footprints to either temperature measures allowing us to capture the heterogeneity in temperature across the U.S. Specifically, we long firms with operational footprints in states with the least exposure to $\widetilde{TA}$ and TAV, and short firms with operational footprints with most exposure to either metric. For each temperature metric, we split 40 states into four quartiles predicated on the realization of $\overline{TA}$ and TAV in each month, t, from February 2006 to December 2019.[12] Each monthly observation for the long portfolio constructed with TAV consists of the ten states that deviated least from their 1960–2005 temperature variability and vice verse for the long portfolio. The short portfolio constructed with TA consists of the states that experienced hotter than normal temperatures in comparison to the states in the long portfolio that sustained colder conditions. After sorting states into quartiles of exposure, the stocks of firms with operational footprints near their headquartered state are partitioned into each quartile at a monthly frequency in order to calculate the value-weighted return of the portfolios. Finally, we subtract the returns from the least exposed sample (first quartile) by the returns of the most exposed (fourth quartile) yielding 167 observations of monthly L/S returns for each temperature metric.

To fix ideas, at time t, the value-weighted return, R, of a quartile portfolio $p = \{1, 2, 3, 4\}$ is:

$$R_{pt} = \sum_{i=1}^{n_{pt-1}} x_{it-1} r_{it}. \tag{6}$$

where r_{it} is the stock return of firm i-th at month t, and n_{pt-1} representing the number of firms in the quartile portfolio p at month $t-1$. x_{it-1} represents the market capitalization of firm i divided by the total market capitalization of portfolio p at month $t-1$.

The central message of our paper can be seen in Figure 6 which plots the long minus short returns of portfolios constructed using $\widetilde{TA}$, denoted by the solid line, and TAV represented by the dashed line. Firms whose operations are unaffected by increased temperature variability enjoy greater cumulative abnormal returns than those with affected operations over the entirety of the sample period. Firm operational footprint, in this case, is defined by the centralization measure in Garcia and Norli (2012) and detailed in Section

We show this relation in numerical form in the first column of Table 2 which reports the mean excess returns net of the U.S. risk-free rate. We also report portfolio alphas adjusted using the Fama-French three-factor model (Fama and French (1993)), which controls for the market factor as well as size and book-to-market factors; the Fama-French-Carhart (Carhart (1997)) four-factor model, which includes Carhart's momentum factor and a fifth liquidity factor (Pástor and Stambaugh, 2003). The middle three quintiles are grouped together by equal-weighting their respective returns.

[12]We remove Alaska, Hawaii, Maine, Montana, New Mexico, Rhode Island, North Dakota, South Dakota, West Virginia, and Vermont from the sample as there only a few firms headquartered in these states. Including these unpopulated states leads to an unbalanced number of firms in each portfolio.

The first column of Table 2 reports the mean value-weighted returns net of the U.S. risk-free rate. We also report portfolio alphas adjusted using the Fama-French three-factor model (Fama and French (1993)), which controls for the market factor as well as size and book-to-market factors; and the Fama-French-Carhart (Carhart (1997)) four-factor model, which includes Carhart's momentum factor. The results reported in the first row of each panel, represent the monthly realized abnormal returns of firms affected by colder temperatures in Panel A and lower volatility of temperature anomalies in panel B. The returns for the middle two quartiles are grouped together by equal-weighting their respective returns and are presented in the second rows. The third rows denote the returns from firms affected by warmer temperatures in Panel A and greater TAV in panel B. Finally, the fourth row presents the realized returns produced from subtracting the portfolio returns of the least affected firms from the most affected.

The portfolio comprising of the least affected firms to TAV in the first row of Panel B, yields a statistically significant abnormal performance of 45 basis points per month or 5.41% per annum (t-stat=2.55) when adjusted with five factors. In comparison, the portfolio if firms that experienced colder than normal temperatures produces a return of 33 basis points per month or 4.03% per annum (t-stat=1.77). The results suggest that the equity market reacts to temperature information and, specifically, that it is pricing the deviations in temperature variability to a greater extent than simply the temperature anomaly. Here, the market is actively rewarding a stable climate over a volatile one and a cooler region over a hotter one.

To contextualize the findings in terms of the literature, our results are in accordance with Addoum et al. (2020) and Addoum et al. (2021) in that there is no market reaction to heat stress as represented by the fourth portfolio quartile in Panel A of Table 2. This challenges the findings of Acharya et al. (2022), Gostlow (2021), and Pankratz et al. (2023) who find a significant negative realized return of firms affected by heat stress although using varied definitions of the term. Our results using TAV are more consistent with the findings of Donadelli et al. (2019) in that there adverse effects of deviations in temperature volatility on average across U.S. based firms as denoted by negative coefficients the third row of Panel B. The average impact of elevated TAV is non-significant because the temperature shock has an heterogenous effect across industries as we describe in the next section. Nonetheless, the economically large coefficients for the portfolio of firms least affected by TAV indicates that the market prefers an invariable environment.

A long-short portfolio strategy using TAV produces returns of 5.54% per annum (t-stat=1.65) in comparison to 1.11% per annum (t-stat=0.37) when exploiting TA. The positive realized performance of the strategy when using TAV over TA suggests that the market has a greater reaction to volatility than deviations to the average. Furthermore, the relation appears to hold across the sample period as illustrated in Figure 6 indicating that either market participants buy unaffected firms and sell the inverse when faced with shocks to temperature variability or that firm performance is tied to TAV. Our empirical exercises test these mechanisms and find evidence of both. Furthermore, we later show a method to construct a portfolio that utilizes the regional heterogeneity of TAV to protect against downside risk.

We perform a battery of robustness checks for our long-short portfolio analysis. First, we show that conditioning on operational area is important. We find that the full sample of the least affected firms to TAV, which includes those with footprints across the U.S., enjoy a more muted but significant annual abnormal return of 4.35% – a difference of a 119 basis points. Second, some states may be systematically exposed to shocks to temperature anomalies or to deviations in temperature variability, forcing some states and firms to be consistently in a certain quartile. Chronic exposure to abnormal temperatures could result in lower returns across the board for firms headquartered in these states. These firms could conceivably be less productive if the state in which they are headquartered is subjected to continual temperature shocks. After constructing a monthly state transition matrix, we show that removing these few states leave the general results unchanged. Third, we consider the absolute value of TA which would treat any deviation from the average temperature as a shock, and thus equally weight abnormally cooler or warmer states. Our findings suggest again that the abnormal returns are greater for the firms in stable environments with no significant effect for those most affected.

Overall, the results from this initial asset pricing test is to show that TAV is a significant factor for the returns of firms that are affected over an above TA. We expect our methodology to *underestimate* the true stock price reaction from temperature shocks due to data limitations. Using granular data on exact firm operations spatially overlaid with TAV would likely lead to greater adjusted returns using this trading strategy.

4.2 Temperature exposure in the cross-section

To examine the equity reaction of affected firms and sectors in more depth, we use a firm characteristic-based asset pricing approach akin to Daniel and Titman (1997) to take advantage of the cross-sectional variation of the firms in the Russell 3000. In comparison to the long-short portfolio methodology, this approach allows us to examine the effects of temperature shocks at the industry level by using time and firm fixed effects. We find that return reactions vary considerably across industries when considering both temperature anomalies and deviations in temperature variability.

We consider the effect of the two temperature metrics, TA and TAV, on the stock returns of firms in the: industrial, energy, health, information technology, utilities, consumer staples, consumer discretionary, materials, financial, and commercial sectors. We run the estimate the following regressions that captures the impact of temperature shocks on stock returns of firms:

$$r_{i,t,s} = \alpha + \beta_T * T_{t,s} + \beta_1 C_{i,t-1} + \phi_t + \eta_i + \epsilon_{i,t} \tag{7}$$

where $r_{i,t,s}$ measures the return of firm i in month t and headquartered in state s. T is a generic term that can stand in for either the deviation of temperature from its historical average (TA), or the deviation of daily temperature variability from its historical mean (TAV). We use the following vector of firm-level controls Cin our cross-sectional regressions: $LOGSIZE_{i,q}$, given by the natural logarithm of firm i's market capitalization (price times shares outstanding) at the end of each quarter q; $B/M_{i,t}$, which is firm i's book value divided by its yearly market cap; $ROE_{i,t}$, which is given by the ratio of firm i's net yearly income divided by the value of its equity; $LEVERAGE$, which is the ratio of debt to book value of assets; capital expenditures $INVEST/A$, measured as the firm's yearly capital expenditures divided by the book value of its assets; $LOGPPE$, which is given by the natural logarithm of the firm's property, plant, and equipment at the end of year t; $MOM_{i,t}$, which in turn is given by the average of returns on stock i, for the 12 months up to and including month $t-1$. To allow for systematic differences in correlations across firms and over time, we include firms fixed effects η_t and year–month fixed effects ϕ_t. In this regard, our identification comes from states' variation in a given month. We cluster standard errors at the firm and year levels, which allows us to account for any serial correlation in the residuals and to capture the fact that some control variables are measured at an annual frequency. Our sample of firms are selected based on our metric of "centralization" developed in Section 2.4.

The results of the regressions for each Global Industry Classification Standard (GICS) sector are presented in Table 3 separated by TA in Panel A and TAV in Panel B. For all sectors except utilities (electric utilities; gas utilities; and multi-utilities), we find economically and statistically insignificant estimates associated with exposure to temperature deviations. Our findings suggest that exposure to warmer or colder than expected months does not exert a substantial positive or negative impact on these industries. Utilities are a special case though, because they are tasked with providing enough energy over time as well as meeting instantaneous electricity demand, while juggling the costs associated with grid balancing and a continuous expansion of non-dispatchable renewable generation. As such, deviations in temperature require utilities to invest more in emergency measures, such as increasing capacity and expanding demand–response investments to mitigate the effects of unexpected changes in daily temperatures. Accordingly, our analysis reflects that the effect of abnormal temperatures on utilities is economically important. The estimate indicates that deviations of the daily temperature from the historical mean are associated with a 10.04 percentage-point decrease in utilities' stock returns, and that this effect is statistically significant.

In Panel B, we examine the effect of changes in the *distribution* of temperature by considering a deviation of daily temperature variability from its historical mean in a given month. As will become clear later, isolating the effect of changes in temperature distribution is decisive for understanding the temperature–stock relationship, and for qualifying some of the findings in previous studies that explicitly consider temperature extremes. Crucially, and in contrast to our estimates for the deviations in (average) temperature, we find that deviations in temperature variability significantly affect energy (oil, gas and consumable fuels; energy equipment), utilities, consumer staples (beverages, food products and tobacco; food and staples retailing; household and personal products) and consumer discretionary services (leisure products; textiles, apparel and luxury goods; hotels and restaurants; beverages; automobiles; and specialty retail).

In Table 4 we rerun the yearly stock return regression by splitting our sample into three time periods, illustrating the robustness of our findings across the following sub-periods: 2005–2009, 2010–2014, 2015–2020. We focus on a small group of sectors that display some interesting patterns: energy, consumer staples, and health care. The first two have significant exposure to TAV over the sample period 2005–2020, see Table 3 Panel B. Table 4 provides the estimates for TA and TAV for these three sectors. We report the results for all other control variables in the Appendix (B). Notably, the effect of TA remains insignificant in each sub-period, confirming the findings over the longer sample period in Table 3. Over time, the estimates of the effect of TAV on the energy sector decrease and then increase, and the estimates are virtually identical for consumer staples. There is no effect of TAV on the health care sector. These results confirm that exposure to temperature varies over time as the distribution of temperature and temperature variability changes over time (Lewis and King (2017), Alessandri and Mumtaz (2021)).

Several channels may be at work to explain the negative impact of deviations in temperature variability on temperature-sensitive industries (Graff Zivin and Neidell (2014), Addoum et al. (2020), Addoum et al. (2021)).[13] Our findings are consistent with the consumer demand and labor productivity channels (Starr (2000); Graff Zivin and Neidell (2014)). Recall that TAV offers a general characterization of the unconditional probability of temperature extremes and, crucially, allows us to (i) simultaneously treat cold snaps and heatwaves as equally detrimental to economic activity, and (ii) capture day-to-day temperature swings between hot and cold. Using this measure, then, we find that many consumer-related sectors, including energy, are affected by changes in temperature variability. For example, large temperature swings can make shopping more or less difficult. Cold snaps and heatwaves can shift consumer demand patterns and may adversely impact what Starr (2000) calls "households' shopping productivity". Starr-McCluer provides empirical evidence consistent with these ideas using sector-level output data. This is also observable when considering macroeconomic output: Colacito et al. (2019) document that extreme heat in summer and autumn months affect U.S. GDP growth rates.

The results in Panels A and B demonstrate the effect of temperature anomaly variability over and above the temperature anomalies highlighting varied investor reaction across industries. Deviation in temperature variability represents a more salient measure of the effects of temperature on equities than temperature anomalies alone. Our measure is therefore a meaningful indicator of physical risk, which has material consequences for the stock price of firms.

5 Attention to temperature shocks

Our prior analysis strongly suggests that exposure to TAV has serious implications for firm stock prices and investors; however, we are agnostic as to the exact mechanism that dictates the price. Theoretically, there are two vectors at play. The first channel is investors' beliefs about companies that are exposed to temperature volatility. Heightened temperature variability acts as a "wake-up call" for investors, drawing attention to the risks of climate change, changing demand and simultaneously moving the equilibrium stock price of the exposed firm. The second, more direct channel, is the tangible, physical realization of the temperature shock on the firm's financial performance (Pankratz et al., 2023). We test the first channel in this section and provide robust evidence that changes in temperature variability have a significant effect on the attention paid by retail and institutional investors.

5.1 Regional attention

To test the first channel, we begin by estimating the relationship between innovations in regional attention indices and TAV and TA. We represent local attention by gathering

[13] These papers examine various channels through which temperature affects economic output: manufacturing and labor productivity are sensitive to high temperatures, destruction of capital may occur at extreme temperatures, and consumer demand tends to drop, coupled with a decreased total labor supply.

state-level Google SVI data on the topics "Climate Change" and "Climate Variability and Change", which should encompass reactions from retail investors and, to a lesser extent, from institutional investors (Da et al. (2011)). Each series gauges the level of interest in a particular topic by calculating the proportion of Google searches on the topic to all searches within a specific state—what Google refers to as a normalized value. The score for the state with the greatest normalized value in the topic is indexed to 100. In comparison to this state, the remaining states are indexed proportionally between 1-100 based on their normalized values of the topic of interest.

Investors should only react to unexpected attention, thus we use the residuals from an autoregressive model with lag one for the state-level indices. Innovations in attention are crucial, as expected attention paid by investors regarding climate change should not move the equilibrium prices of assets.[14] Investors should react to unexpected temperature swings by selling the exposed firm accordingly.

To test the relationship between unexpected changes in climate change attention and temperature volatility, we regress innovations indices on TAV and TA along with various fixed effects:

$$\epsilon_{AttentionIndex,s,t} = \alpha + \beta_T * TAV_{s,t} + \beta_D * TA_{s,t} + \rho_t + \gamma_s + \epsilon_{s,t}. \tag{8}$$

where the dependent variable is the AR(1) innovations of a specified Google search topic in a particular state, s. ρ_t and γ_s represent time and state fixed effects, respectively, and are included in the model when needed. All models include standard errors that are clustered by state to account for serial correlation of the error term within the state. Clustering, in this case, is performed at the level of treatment, which is at the state level.

Table 5 reports the results of the U.S. state-level regressions providing evidence that β_T is positive and significantly different from zero. The coefficients of TAV in columns 1 and 4 are at least significant at the 5% level, indicating a contemporaneous relationship between shifts to temperature volatility and Google search interest for the topics "Climate Change" and "Climate Variability and Change". When TAV increases by one standard deviation (0.48), there is an associated increase of 0.37 in unexpected Google searches for the topic, "Climate Change", for the most saturated model in column (3). In this model, we use state and time fixed effects to control for omitted variables that are constant either over time or across states. In panel (b), the low r-squared values across columns suggest that the topic, "Climate Variability and Change", is more difficult to explain than its counterpart. Nonetheless, we show that TAV is significantly associated with the topic when using variation within states, i.e., the results presented in column (5). However, adding both year and quarter fixed effects cuts the coefficient by more than half, likely due to the variation captured by additional fixed effects.

The second row of Table 5 presents the estimated values of β_D, the coefficient on TA. In the most saturated specifications of Table 5, i.e., columns (3) and (6), we show that TA is not significantly associated with innovations in either index. This result suggests that deviations to the first moment of temperature anomalies is not a meaningful driver of state-level attention. The more interesting finding is the negative relationship between

[14] An investor's trading actions are 'conditioned' on their expectations of future climate shocks. However, unexpected shocks that are observed by investors may lead them to update their investments.

TA and attention across all specifications, denoting that warmer temperature anomalies decrease the intensity of searches for either search topic. This relationship implies the opposite as well—colder anomalies are associated with greater attention paid by local residents or investors. Simply put, these results suggest that colder rather than warmer temperatures shift unexpected investor attention, indicating that warmer temperatures are expected and therefore are not related to greater unexpected attention to climate change.

At face value, the findings that TA fails to shift unexpected attention conflict with the results of Deryugina (2013) who show that warmer-than-normal temperatures strengthen the belief of global warming amongst US adults between 2003-2010. The earlier sample of Deryugina (2013) could suggest that heat shocks were unexpected during this period; however, climate change has become popularized after the first decade and therefore could be considered as "expected". Goldsmith-Pinkham et al. (2022), for example, find that sea level rise—a significant physical risk—has only been priced from 2010 on. Another reason could be that only "extreme" heat events shift unexpected attention. We test for both of these hypotheses in our robustness checks and find no empirical evidence for either mechanism.

5.2 National attention

Next, we examine the effect of TA and TAV on broader national attention to climate change. To do so, we adopt the innovations of the WSJ climate news index as our aggregate climate attention measure, as developed by Engle et al. (2020). Engle et al. (2020) build the index from WSJ news articles that contain a discussion on climate change. Specifically, their measure captures the intersection between the news article text on climate change and the primary governmental or research source on which the article is based. Their assertion is that news articles on climate change are published more frequently when climate concerns are apparent. Their narrative index connects an increase in news coverage of climate change with a heightened awareness of climate risks among investors.

For our empirical exercises, we again use specification denoted in equation 8 with the innovations in the WSJ news index as the dependent variable. We aggregate TA and TAV by the median value across all states to obtain a time series for both metrics—essentially removing the notation s in equation 8. Performing a simple correlation between TAV and the innovations in the WSJ news index produces a Pearson coefficient of 22.9%, indicating a moderate positive relationship with the index. Performing the s the same exercise with TA gives rise to a much weaker, negative coefficient of -7.8%.

Table 6 provides the regression results indicating that TAV has a moderate relationship with the publication of climate-related news across the US. Specifically, we find positive and significant coefficients on TAV when using pooled ordinary least squares, denoted in column (1), and using seasonality fixed effects in column (2). In the most saturated specification in column (3), we find a positive but not statistically significant relationship. The coefficient remains large and the lack of significance is likely caused by the minimal variation remaining after including time fixed effects. We uncover a non-significant but negative relationship between TA and innovations in the WSJ news index, presented in the second row of Table 6. These results suggest that the number of unplanned articles written about climate change are positively and contemporaneously correlated with TAV rather than TA.

Synthesizing the results from the empirical exercises testing the relationship between temperature shocks and attention, we conclude that TAV is positively associated with unexpected state- and country-level attention towards climate change over and above TA. The larger effect size of TAV substantiates our claim that this is the more salient metric. We contend that unexpected swings in temperature variability grab the attention of news agencies and, subsequently, investors across the nation. However, we are agnostic as to the type of investor, as well as to whether investors do in fact read the articles that are published, as attention is a scarce resource. Nevertheless, the results thus far imply that investors are affected by elevated news coverage of climate risks, which lead to the pricing effects seen in our asset pricing tests. This attention channel is one explanation of why investors reallocate their portfolios.

5.3 Earnings call participant attention

The previous empirical results demonstrate a significant shift in attention towards climate change, more generally, in response to changes in temperature variability. Explicitly, the mechanism is that TAV acts as a precursor to investors—either retail or institutional—incorporating the new information into their investments. We illustrate in this section that earnings call participants, sophisticated investors, analysts, and managers, spend more time discussing firms that are affected by shocks to temperature variability.

We adopt a physical climate exposure measure by Sautner et al. (2023) who use these earnings call transcripts to develop a time-varying measure of firm-level exposure to physical climate change risks. Specifically, we use their measure, $CCExposure^{Phy}$, which captures firm physical climate exposure because temperature shocks are a realized form of a physical climate shock. Their methodology consists of using physical climate related bigrams, i.e., two word combinations, to sift through sentences and measure the discussion of physical climate topics as a fraction of all other topics. Bigrams related to physical risk include word combinations such as "air temperature", "global warm", and "sea level". While the universe of bigrams used in Sautner et al. (2023) do not completely match the risks of TA and TAV, we maintain that there is enough similarity between these metrics and $CCExposure^{Phy}$.

Akin to our prior regressions using the innovations in attention indices, we obtain the AR(1) residuals of $CCExposure^{Phy}$ and use $\epsilon_{CCExposure^{Phy},i,t}$ as a measure of unexpected attention to physical climate risks. Our empirical specification regresses these innovations on TAV and TA with firm fixed effects:

$$\epsilon_{CCExposure^{Phy},i,t} = \alpha + \beta_T * TAV_{s,t} + \beta_D * TA_{s,t} + \beta_g * WSJ_t + \beta_m * \epsilon_{WSJ,t} + \gamma_i + \epsilon_{i,s,t}. \quad (9)$$

for firm i at time t headquartered in state s. Although the transcript data is available at a quarterly frequency, we use a yearly sample as the data contains significantly fewer non-missing values. The main variation occurs at the state-year level, as this is where firms are exposed to time-varying temperature shocks. Our assumption here is that the operational footprint of the firm is located in the headquartered state.

In addition to the temperature metrics, we include the WSJ news index (WSJ_t) and its innovations ($\epsilon_{WSJ,t}$) by taking the average of each series over a year. There is considerable overlap between attention and climate discourse as both investors and management may raise the issue during periods of global attentiveness. The results of Sautner et al. (2020) confirm this view, finding a positive relationship between the WSJ index developed by Engle et al. (2020) and their physical climate measure. We include both "expected" and "unexpected" series as they both could contribute to greater attention paid during the call.

Table 7 presents the regression results for the full sample of firms in panel (a) and firms screened by the centralization methodology in panel (b). All columns produce a statistically significant association with TAV and firm-specific attention to physical climate exposure for all firms. We interpret these results as TAV being associated with an increase in the proportion of an earnings call that discusses physical climate change exposure. The coefficients associated with the variable TAV retain their statistical significance after accounting for the influence of both anticipated and unanticipated climate attention at the national level. This suggests that shocks to temperature variability are a contributing factor in participants' concerns regarding physical exposure to climate change, coexisting with the impact of climate-related news articles. Probing the results further, we underscore that the treatment is at the firm level. Therefore, earnings call participants—who may or may not be in the affected state—are savvy enough to observe shocks occurring in the firm headquarter. There are no significant coefficients on TA across all specifications suggesting that shifts in average temperature are not consequential enough to discuss during earnings calls.

Using only firms that are concentrated near their headquarters reduces the magnitude and significance of the coefficients related to TAV in Table 7. One reason for this result could be that firms with geographically broader production networks are more often affected by temperature shocks simply due to the breadth of their networks. These events are salient enough to be noticed by analysts resulting in more frequent mentions of physical risks during earnings calls.

In sum, the empirical findings are coherent with our results in Sections 5.1 and 5.2, which suggested that TAV is a consequential driver of investor attention. Moreover, we uncover here that a shock to temperature variability is salient event for sophisticated market participants.

6 Temperature exposure and firm performance

We next empirically test whether temperature shocks, measured by our two metrics TA and TA, affect performance for firms in the Russell 3000. Our prior asset pricing tests confirm a synchronous equity reaction by the broader market to shocks to TAV and we continue by measuring the material impact, if any.

Our focus is on understand the effects of the two metrics on accounting variables such as revenues, sales, expenses, and, plant, property, equipment—all variables that could reasonably be affected by temperature shocks. Our identification strategy, similar to that of Pankratz et al. (2023), is to use the plausibly exogenous TAV and TA and estimate their effects on the accounting variables using regressions that control for firm and time heterogeneity. Our saturated models sidestep the issue of "bad controls" (Angrist and Pischke, 2008) by only using fixed-effects instead of accounting variables as controls because temperature could realistically impact other line-items. Our specifications can be described as follows:

$$\frac{\text{line item }_{\text{i,s,t}}}{\text{assets }_{\text{i,s,t}-4}} = \alpha + \beta_T * TAV_{s,t} + \beta_D * TA_{s,t} + \gamma_i + \rho_t + \epsilon_{i,s,t}. \tag{10}$$

where *lineitem* represents an accounting variable for firm i, headquartered in state s, in a year and fiscal quarter t. The line items of interest are divided by total *assets* in order to control for firm size, but lagged by four quarters to remove the issue of temperature shocks potentially affecting total assets. We include firm and time (year-quarter) fixed-effects by denoting γ and ρ, respectively. Similar to our prior regressions, we cluster our standard errors at the treatment level, the state headquarter of a firm. The sample of firms only include the firms that are centralized around their headquarters in order to capture the direct effect of the temperature shocks on firm operations.

Table 16 shows TAV has negative but non-significant effect on the revenues of affected firms across all industries; however, the results are more interesting when leveraging industry heterogeneity. We split the sample based on our industry specific, cross sectional regression results, into: consumer discretionary and consumer staples, utilities, and energy. In the second column of panels (a) and (b) we illustrate a negative relationship between TAV and total revenues driven entirely by the loss of sales in these industries. On the other hand, there is no significant effect of TA on revenues. These results align with Addoum et al. (2020) who find no material effects of abnormal temperatures on establishment sales.

The results are easily interpreted through an economic lens because the dependent variable, revenues over total assets, is a classical measure of firm efficiency. For firms in the consumer discretionary and staples sectors, a one-standard deviation increase in TAV is associated with a moderate 48 basis point decrease of the ratio. An example of a firm in this sector is the Hershey Company which has three of its six manufacturing plants and multiple theme parks located in Pennsylvania. The estimated relationship implies that sales are reduced during a quarter with greater deviation from its historical temperature variability. In Table 9, we analyze the income statement and expenses of affected firms which adds context to these findings on the balance sheet. Interestingly, we find a negative relationship with total operating expenses for the consumer discretionary and staples sectors, driven by decrease in the cost of goods sold. In standard accounting for firms with physical goods, the cost of goods sold for a period is calculated by subtracting the ending inventory by the sum of beginning and new inventory. Connecting the results from the balance sheet and income statement, the results point to a situation where firms have difficulty in selling goods, affecting returns over assets, which leads to an increase in the ending inventory.

The balance sheet and income statement of energy firms demonstrate a stronger reaction to the impacts of TAV on firms within the consumer discretionary and staples sector. The operations of energy firms in this sample largely consist of oil, gas, and mineral extraction. A one-standard deviation increase in TAV leads to a 14.7% decrease in the ratio of sales over lagged total assets for affected firms. These firms record revenue when a product, e.g. a barrel of oil, is delivered to a customer and does not record revenue when they fail to meet the obligations of their customers. An example of such a company is Brigham Minerals, Inc which acquires oil and gas rights and leases out tracts of land to third party operators to extract natural resources in Texas and nearby states. The third party operators bear the costs of production and exploration and directly pass through these costs to the revenues of Brigham Minerals. In this setting, the loss in revenues can therefore be interpreted as the costs of production and exploration increasing for the lessees when temperature variability increases. In the results of the income statement in Table 9, we find that cost of goods sold decreases implying that ending inventories increase with respect to beginning inventories.

An interpretation of this relationship is that TAV impairs the transportation of the physical goods of the lessees, leading to a greater number of goods that are unable to reach their intended customers.

Lastly, we analyze the effects of temperature shocks on gross plant, property, and equipment (PPE) normalized by lagged total assets in Table 10. PPE is of particular interest as it captures physical equipment, structures, construction, and land—assets that are susceptible to degradation stemming from increased temperature variability. Column (1) shows a significant, negative relationship between TAV and PPE for all industries—specifically, a one-standard deviation increase in TAV is associated with 40 basis point decrease in PPE. For the consumer discretionary and staples sectors, we find a slightly larger effect of 52 basis points with a one-standard deviation shock to TAV. These estimated relationships suggest that increased temperature variability devalues the physical assets of affected firms ultimately affecting their total assets and requiring them to invest in more resilient infrastructure. Once more we find that deviations to average temperature anomalies have no significant effects to firms' PPE.

Our findings extend the prior the literature, focusing on abnormal heat or cold, by showing that shocks to temperature variability have a significant effect on firm revenues and expenses. Combining our prior results on attention, we show that investors are right to be concerned about the effects of TAV on firm operations. Similar to Addoum et al. (2020), we find a null effect of abnormal temperatures on balance sheet and income statement line items.

7 Practical Utility of TAV: Examples of Measuring and Reporting Temperature Risks

In a recent Financial Times article, it was underscored that businesses and investors seem to prioritize the costs and risks of decarbonization over the tangible impacts of physical climate change (FT (2023)). This disparity is evident, as US corporate disclosures address the physical repercussions of climate change only half as frequently as decarbonization topics, based on findings from the Brookings think-tank.[15] A significant reason is that much of the disclosure reflects the risks that are easiest to quantify. Transition risks, which pertain to the financial implications of the global shift towards a low-carbon economy, are more straightforward to measure than the complex physical risks posed by climate change. Moreover, the heightened focus on transition risk aligns with the prevailing understanding of how financial assets might be impacted by climate policies. In essence, it's easier for businesses to wrap their heads around policy-driven financial implications than the physical threats of a changing climate.[16]

This trend has not gone unnoticed by regulatory bodies. Companies are now under mounting pressure to disclose climate-related financial risks. This comes in the wake of proposals from regulatory agencies such as the Securities and Exchange Commission and the European Financial Reporting Advisory Group. These bodies are pushing for rules that would mandate companies to include specific climate-related disclosures in their financial statements. This would encompass information about climate-related risks that could materially impact their operations or financial health, along with certain climate-related financial metrics in their audited financial statements. Recently, the European Commission took a significant step in this direction by adopting the European Sustainability Reporting Standards (ESRS).[17] This regulation will eventually mandate all listed companies operating within the EU to disclose the climate's impact on their operations. However, while the ESRS has clear and specific mandatory reporting requirements for transition risks, such as direct and indirect emissions, energy intensity, and energy consumption, it lacks clarity on the potential metrics for reporting financial effects arising from physical risks. The standards are also unclear about the methods to be used for reporting and evaluating exposure to climate physical risks.

[15] Currently, a significant portion of publicly traded companies disclose some information related to climate change. The majority of this information pertains to risks associated with transitioning away from fossil fuels. However, there is a noticeable lack of disclosure regarding the physical risks of climate change, especially the impacts of temperature changes.

[16] An expanding body of research has centered on transition and regulatory risk, establishing that investors command higher returns and require a premium (Bolton and Kacperczyk, 2021; Cheema-Fox et al., 2020; Görgen et al., 2020; Hsu et al., 2022; Lioui, 2022), that the market demands changes in the capital structure (Nguyen and Phan, 2020; Kleimeier and Viehs, 2018), and that engagement effort concentrates on large firms with high carbon emissions (Azar et al., 2021).

[17] The European Commission adopted a legislative proposal for a Corporate Sustainability Reporting Directive (CSRD) in 2022, which entered into force on January 2023 and requires companies to report on climate metrics relevant to both their own climate-related transition risks, as well as their impact on the planet. The CSRD updated the bloc's Non-Financial Reporting Directive (NFRD) and the Accounting Directive to obligate more types of companies to report on climate and sustainability metrics. The ESRS specifies the information that needs to be included under the CSRD. The CSRD also requires the Commission to adopt standards for non-EU companies by June 2024.

In this section, we explore the ramifications of our research findings on the processes of measuring and reporting physical climate risks. This exploration is crucial for both corporations and investors, as understanding these risks can significantly impact decision-making and strategic planning.

To underscore the practical utility of our measure in disclosing potential exposure to physical climate risks, we embark on two distinct exercises. The first exercise contemplates a scenario where a company discloses whether its exposure to temperature variations is trivial or significant. Such disclosure can provide invaluable insights to policymakers and stakeholders about the extent of a firm's vulnerability to physical climate risks. This exercise is in harmony with the guidelines set forth by the Task Force on Climate-related Financial Disclosures (TCFD). According to TCFD principles, a company's disclosure of climate exposure should accurately represent the potential disruptions its operations might face due to specific physical risks. For this exercise, we employ TAV projections, treating them as a conventional risk factor typically used in risk management endeavors (Meucci 2005).

There are two potential methodologies to approach this: the historical simulation and the forecast-driven projection. The historical simulation is relatively straightforward, operating under the assumption that the forthcoming TAV value will mirror its predecessor. The forecast-driven projection, on the other hand, is more intricate. It necessitates projecting daily temperatures for various US states and then applying expressions (1-4) to estimate the TAV for the upcoming year. We embrace the forecast-driven projection methodology, leveraging future-oriented projections sourced from specific research studies.

In our analysis, we conceptualize a hypothetical firm that operates fourteen distinct installations situated in four separate states: Arizona, California, Colorado, and Iowa. To assess the potential temperature risk exposure of this firm, we generate annual TAV values for each of these states. TAV, as a measure, provides insights into the temperature anomaly variability, which can be indicative of the physical risks associated with climate change. By combining this TAV data with specific information about the firm's installations – such as their precise locations and the nature of operational activities conducted there – we can gauge the potential impact of temperature anomalies on the firm's operations. Now, with this combined data, the firm can categorize its installations based on the level of risk they face due to temperature anomalies. For instance, installations in areas with high TAV values might be categorized as 'high risk', while those with moderate values might fall under 'medium risk'. To provide a comprehensive view of its risk exposure, the firm can then compute the percentage of its installations that fall within each risk category. This would allow stakeholders to understand, at a glance, the proportion of the firm's operations that are at high or medium risk due to temperature anomalies.[18] Table 11 serves as a practical representation of this hypothetical reporting exercise. The table categorizes installations into three distinct risk levels: high, medium, and low. These categories are determined based on the projected TD-VAR values for the subsequent year. For each risk category, the table displays the percentage

[18]While a straightforward approach would be to calculate this percentage based on a simple count of installations in each category, a more nuanced method might involve weighting the installations based on certain operational metrics. For instance, an installation that houses a significant portion of the firm's workforce or contributes a substantial amount to its sales might be given more weight in the computation. This weighted approach ensures that the computed percentages reflect not just the number of installations at risk, but also their relative importance to the firm's overall operations.

of the firm's installations that fall within that category. This provides stakeholders with a clear and concise overview of the firm's potential exposure to climate risks, serving as a model for how businesses can effectively report on ESRS and TCFD.

In the second exercise, we shift our lens to view the implications of temperature variability from an investor's vantage point. Investors, with their stakes in multiple firms spanning various sectors, need a comprehensive measure to gauge the potential risks (and returns) associated with their investments. The sector-portfolio-adjusted TAV emerges as a pivotal metric in this context, offering insights into a portfolio's susceptibility to temperature variability. The rationale behind emphasizing the sector-portfolio-adjusted TAV is rooted in the sector-specific nuances we have uncovered in our earlier discussions. Different sectors, given their unique operational dynamics, exhibit varying degrees of vulnerability to temperature fluctuations. For instance, the Consumer Discretionary sector might be more immediately and severely impacted by temperature anomalies compared to the Health sector. Thus, a holistic assessment of portfolio risk necessitates a deep dive into these sectoral intricacies.

To operationalize this, an investor would begin by segmenting their portfolio based on sectors. The spotlight would then be cast on sectors that are particularly sensitive to temperature variability. For each identified sector, the investor would then compute the TAV, but with a twist. Instead of a blanket approach, the TAV would be weighted based on the geographical location of the firms' headquarters. This is crucial because temperature variability is inherently spatial, with some regions experiencing more pronounced fluctuations than others. The resultant metric, the sector-specific TAV, encapsulates both the sectoral and geographical dimensions of risk.

To translate this metric into actionable insights, investors can draw parallels with historical data. For instance, if past trends indicate that a 1% underperformance in the energy sector corresponds to a TAV of, say, 5%, investors can set their expectations and strategies accordingly. Table 12 encapsulates this analytical process, presenting the TAV computations for a representative portfolio. By integrating sectoral and geographical nuances, this table offers investors a granular view of their exposure to temperature variability, empowering them to make informed decisions in an era where climate considerations are increasingly intertwined with financial outcomes.

The two exercises presented in this section underscore the applicability of our temperature metric in the realm of climate physical risk reporting.

8 Robustness Checks

8.1 Temperature exposure and weather derivative pricing

The relevant impact of weather on electricity demand has facilitated the creation of a market for weather derivatives. This market enables utility firms to hedge volumetric risk by trading the underlying risk driver – temperature – rather than the price of electricity (Jewson and Brix (2005)). We further validate our temperature measures by testing their association with city-level temperature derivatives prices.

We hypothesize that, if traders account for deviations in temperature volatility, TD-VAR should capture more variation in weather derivatives prices than TD. To verify that our measure is relevant for weather derivative markets, akin to Diebold and Rudebusch (2019), we analyze futures contracts offered by the CME. The key benefit of this approach is that Schlenker and Taylor (2021) find that market participants accurately incorporate temperature anomalies through climate model projections. We extend this line of thought to confirm whether $TD\text{-}VAR$ is a driver of these contract prices. The first contract follows HDDs, which reflects the amount of heating required during cold days in winter. The second tracks CDDs that measure the necessary cooling required during hot days in summer. Therefore, CDDs have effective values in summer and HDDs in winter. We strictly define CDDs and HDDs where T_0 is set at 65°F for a contract traded at the CME:

$$\begin{aligned} CDD_{i,m} &= \textstyle\sum_{d=1}^{D_m}(T_d - T_0)^+ \\ HDD_{i,m} &= \textstyle\sum_{d=1}^{D_m}(T_0 - T_d)^+. \end{aligned} \tag{11}$$

We use ordinal least square (OLS) regression analysis to investigate whether monthly average prices for CDDs and HDDs are affected by temperature – measured as temperature deviation and deviation in temperature variability. We estimate CDDs and HDDs separately with the following equations:[19]

$$\begin{aligned} CDD_{s,m} &= \beta_t T_m + \beta_e \widetilde{TD}_t + \beta_v TD\text{-}VAR + \beta_v \sigma(TD) + \gamma_m + \eta_s + \epsilon \\ HDD_{s,m} &= \alpha + \beta_t T_m + \beta_e \widetilde{TD}_t + \beta_v TD\text{-}VAR + \beta_v \sigma(TD) + \gamma_m + \eta_s + \epsilon, \end{aligned} \tag{12}$$

where T_m is the average daily temperature level minus 65°F degrees and $\widetilde{TD}$, $\sigma(TD)$, and $TD\text{-}VAR$ are defined in Section (**??**). For month and state fixed effects, we include γ_m and η_s, respectively. We only consider the constant term in winter given that the contract is not written on the maximum temperature of 65°F. We split the contract data into winter (October to March, inclusive) and summer months (April to September, inclusive).

Table 14 shows the results for the two contracts using various temperature drivers. The first column of each panel includes the underlying temperature on which the contract is written, while the second column includes the other volatility measures. We show that T_m alone is able to explain 90% of monthly average price variance for CDDs in summer and 95% for HDDs in winter. An increase in temperature results in a decline in the price of CDDs, and vice versa for HDDs. Unsurprisingly, the magnitude of the coefficients is similar and of opposite sign, given that the derivative is dependent on the deviation from the 65°F threshold.

We then consider the remaining statistics: $TD\text{-}VAR$, $\widetilde{TD}$, and $\sigma(TD)$. We document that historical variability, $\sigma(TD)$, has a large significant coefficient during the winter but no effect in summer. The result supports the findings in prior literature that temperature volatility is greater during these months.[20] The coefficients for $TD\text{-}VAR$ are comparable across winter and summer, which is intuitive when recalling the option price effect of the volatility on the underlying asset. Higher deviations in temperature variability from the

[19] We use the derivatives defined in Section **??**, and only consider the seven cities for which the derivatives are still traded.

[20] Examining the seasonal component of temperature volatility, Campbell and Diebold (2005) and Benth and Benth (2007) document the higher values of temperature volatility during winter times.

historical mean increase the probability of experiencing extreme temperatures and, consequently, increase the probability of exercising the option, thereby increasing the value of the weather derivative contract. This indicates that two cities with comparable average temperatures may face diverging weather derivatives prices when one city is characterized by higher temperature variability. Finally, we compare the coefficients of TD which have signs in the opposite direction to T_m. This suggests that traders assume temperatures will revert back to their historical levels when a city experiences higher temperature deviations. Collectively, we find that traders react negatively to increasing TD-VAR by establishing a higher price for the apparent risk, whereas an increase in TD implies a reversion to the mean for the market.

Our validation exercises strongly suggest that shifts in temperature variability, TD-VAR, are primary drivers of electricity consumption and the weather futures market. The results are consistent with Diebold and Rudebusch (2019) in demonstrating that refined measurements of temperature extremes can be consequential for financial asset prices. This confirmatory evidence also suggests that we are better able to characterize the reactions of market participants using deviations in temperature variability than by referring to temperature deviations alone. We continue this line of reasoning by asking whether this market response to TD-VAR has further implications for the stock market.

8.2 Temperature exposure and electricity consumption

Our prior examples reveal that the TD-VAR measure compares favorably to TD in capturing the incidence of temperature extremes. Next, we test the salience and validity of our measure, TD-VAR, by investigating whether deviations in temperature variability are a relevant driver of energy consumption and prices in the weather derivatives market. This follows prior research by Campbell and Diebold (2005), who document that *unexpected* weather fluctuations can cause substantial pricing effects on the weather derivatives market and its players, such as energy producers and consumers. Given that TD-VAR captures extreme fluctuations in temperature, we expect TD-VAR to perform better than TD at accounting for variations in energy consumption and weather derivative prices.

We begin by examining the effect of $\widetilde{TD}$ and TD-VAR for energy consumption. We obtain time-series data on energy demand at the monthly frequency from the U.S. Energy Information Administration for all states. Energy consumption is classified by sector: residential, commercial, industry and transportation. Since energy consumption displays strong seasonal patterns, our analysis focuses on modeling short-run temperature shocks not captured by long-term trend analysis (Son and Kim (2017)). We link the observed seasonality of monthly demand (Bigerna (2018)) to the two components of temperature: anomalies and deviation in variability. We first run an ARMA (J,P) for each state s following Bigerna (2018):

$$Q_{s,t} = \sum_{j=1}^{J} a_j Q_{t-j} + \sum_{p=1}^{P} b_p \epsilon_{t-p} + \epsilon_{s,t} \tag{13}$$

where $Q_{s,t}$ represents the electricity consumption in state s at time t, J is the autoregression order and P is the moving average order. We then check the significance on the residual against TD-VAR and TD respectively, and estimate a fixed effects model:

$$\epsilon_t = \beta_v * TD\text{-}VAR + \beta_t * \widetilde{TD} + \gamma_t + \eta_n + \epsilon. \tag{14}$$

Table (15) shows the resulting coefficients. We observe a positive and statistically significant β coefficient for the deviation in temperature variability, $TD\text{-}VAR$, in residential and industrial sectors and in the aggregate. A positive coefficient implies that, in a month characterized by high variability, the forecast value of electricity consumption exhibits a larger error relative to the best-fit value estimated through Equation (13). This error is inherently determined by the extent of the variability. The non-significant coefficient for $TD\text{-}VAR$ in the commercial sector suggests that the elasticity of electricity consumption is different for the residential and commercial sectors. This conclusion is supported by Zachariadis and Pashourtidou (2007) who find that the residential sector is highly reactive to weather conditions, as demand in the short term is inelastic to price. Taken together, our results confirm prior evidence of energy consumption being highly affected by weather conditions (Quayle and Diaz (1980)) and sensitive to large shifts in temperature variation. (Chang et al. (2016)).

9 Conclusion

Extreme temperatures have been found to modulate financial markets. Furthermore, climate scientists have found that the distribution of temperature anomalies is becoming broader with an asymmetric lengthening of its tails (Hansen et al. (2012)). Using these facts as our motivation, we derive a metric, $TD\text{-}VAR$ which represents the deviation of the unconditional volatility from its historical level. We confirm the saliency of the metric on financial markets by using its monthly and annual realizations. At all stages, we compare our statistic to a widely accepted form of extreme temperature realizations: temperature anomalies or TD.

Through a set of empirical exercises, we demonstrate that shifts in $TD\text{-}VAR$ are primary drivers of: (1) energy consumption, (2) weather futures, and (3) U.S. stock markets. When we execute a hedging strategy by incorporating differential firm exposure, we find substantial market-adjusted returns suggesting excess return predictability. Finally, we investigate the underlying mechanisms and show that the observed pricing effects occur due to a combination of investor attention and firm-level repercussions as a result of changes to $TD\text{-}VAR$ rather than TD.

Our results have considerable implications for the energy and utilities sectors which are sensitive to day-to-day temperature variability as well as heat and cold waves. While we find a moderated effect on consumer sectors, we believe that a larger effect size would be found with the inclusion of more granular footprint data to better identify firm exposure. We leave this for future research.

The statistical methodology outlined in the paper can be readily scaled and replicated to assess the physical risk of other geographic regions. Furthermore, TD-VAR can serve as a reference of physical risks in the disclosures of organisations to better measure the exposure of their operations. Specifically, the metric can be applied to evaluate *acute* climate risks - a recommendation set out by the Task Force on Climate-related Financial Disclosures.

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10 Tables

Table 1: Summary Statistics, Russel 3000

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
LOGSIZE	9.18	9.21	9.08	8.97	9.10	9.17	9.18	9.28	9.34	9.34	9.32	9.40	9.43	9.42	9.40
B/M	12.88	14.38	15.03	13.69	13.99	14.55	14.45	14.99	15.69	16.11	15.69	15.91	16.75	17.14	17.82
ROE	11.25	9.04	-1.38	3.05	7.17	7.79	7.77	8.22	6.87	3.48	3.60	5.14	3.96	0.92	-4.59
INESTA	20.15	20.31	21.01	23.03	22.07	21.66	22.62	23.63	23.12	24.31	25.48	25.60	25.32	25.51	24.85
DEBTA	23.92	24.10	24.92	27.34	25.76	25.06	26.18	27.04	26.17	27.22	28.34	28.80	28.31	28.37	27.72
INVEST/A	5.92	5.64	4.86	3.45	4.13	4.99	4.92	4.77	4.74	4.42	4.08	4.10	4.24	4.02	3.02
LOGPPE	8.19	8.22	8.25	8.26	8.25	8.26	8.26	8.26	8.24	8.24	8.25	8.26	8.27	8.28	8.39
MOM	1.26	0.23	-3.78	3.57	2.09	0.58	1.48	3.03	0.89	0.45	1.16	1.68	0.27	1.03	1.94

The table provides summary statistics for the control variables of the components of the Russell 3000 index. Each component is given equal weight each year. 'LOGSIZE' refers to the natural logarithm of the market capitalization, which is the total market value of a company's outstanding shares of stock. 'B/M' is the ratio of a firm's book value (the value of a company's assets that shareholders would theoretically receive if a company were liquidated) to its yearly market capitalization. 'ROE' stands for Return on Equity, which is the ratio of a firm's net yearly income divided by the value of its equity. 'LEVERAGE' is the ratio of debt to the book value of assets. 'INVEST/A' represents the firm's yearly capital expenditures (the funds used by a company to acquire or upgrade physical assets such as property, industrial buildings, or equipment) divided by the book value of its assets. 'LOGPPE' is the natural logarithm of the firm's property, plant, and equipment. 'MOM' is the average of returns on stock for the 12 months up to and including month $t-1$.

Table 13: Specification of city dataset

City	GHCND Code	State	Weather Derivative	Mean	Std
Atlanta	GHCND:USW00013874	Georgia	X	72.0	15.3
Boston	GHCND:USW00014739	Massachusetts		59.3	18.4
Baltimore Washington	GHCND:USW00093721	Maryland		65.6	18.6
Cincinnati	GHCND:USW00093814	Ohio	X	63.8	19.7
Chicago	GHCND:USW00094846	Illinois	X	59.0	21.5
Dallas Forth Woot	GHCND:USW00093904	Texas		79.6	16.1
Des Moines	GHCND:USW00014933	Iowa		60.2	22.7
Detroit	GHCND:USW00014822	Michigan		58.7	20.7
Las Vegas	GHCND:USW00023169	Nevada	X	80.2	18.5
Minneapolis	GHCND:USW00014922	Minnesota	X	54.9	24.1
New York La Guardia	GHCND:USW00014732	New York	X	62.3	18.4
Portland	GHCND:USW00024229	Oregon	X	63.0	14.5
Philadelpia	GHCND:USW00013739	Pennsylvania		64.4	18.8
Salt Lake City	GHCND:USW00024127	Utah		64.3	21.2
Tucson	GHCND:USW00023160	Arizona		83.2	14.9

The table outlines the details of the cities for which we have obtained daily Global Historical Climatology Network (GHNC) data from the U.S. National Oceanic and Atmospheric Administration (NOAA). The data collection points correspond with the airports of these cities. The column labeled 'Weather Derivatives' indicates the cities for which a Cooling Degree Days (CDD) or Heating Degree Days (HDD) weather derivative is traded on the Chicago Mercantile Exchange (CME). Mean and Std are the summary statistics related to the temperature levels in Fahrenheit Degrees(°F).

Table 2: Abnormal returns to portfolios sorted on temperature metrics for geographically concentrated firms

Panel A: Portfolios sorted on TA

	Excess Return	3-Factor	4-Factor	4-Factor + Liq
Quartiles 1	1.0761***	0.3338*	0.3348*	0.3365*
	(2.8411)	(1.7856)	(1.7846)	(1.7726)
Quartiles 2 and 3	0.7279**	0.0240	0.0227	0.0227
	(2.2627)	(0.3278)	(0.3099)	(0.3099)
Quartile 4	0.8771**	0.1521	0.1447	0.1468
	(2.5520)	(0.9633)	(0.9323)	(0.9506)
Quartile 1 - 4	0.1049	0.0861	0.0944	0.0927
	(0.4117)	(0.3427)	(0.3788)	(0.3704)

Panel B: Portfolios sorted on TAV

	Excess Return	3-Factor	4-Factor	4-Factor + Liq
Quartiles 1	1.1575***	0.4334**	0.4419**	0.4510**
	(3.1815)	(2.4354)	(2.4802)	(2.5503)
Quartiles 2 and 3	0.7909**	0.0839	0.0839	0.0845
	(2.5229)	(1.3017)	(1.3017)	(1.3032)
Quartile 4	0.6131	-0.1270	-0.1253	-0.1082
	(1.5969)	(-0.6356)	(-0.6228)	(-0.5439)
Quartile 1 - 4	0.4503*	0.4648*	0.4717*	0.4622*
	(1.6825)	(1.6619)	(1.6786)	(1.6566)

t-stats reported in parentheses
***1% significance,**5% significance, *10% significance,

Table (2). The sample period is from 2006 to 2020. It reports the alpha (in percentage) to quintile portfolios sorted on TA (Panel A) and TAV (Panel B). At the end of each month t, we sort states into quintile portfolios based on their TA and TAV, separately, using data up to month t. Returns for each quintile portfolio is the value-weighted returns of the firms headquartered in each state. Quintile 1 are those U.S. states with the lowest values of temperature deviations TA (Panel A); and lowest value of deviation of temperature variability TAV (Panel B). Quintile 5 are those countries with the highest values of temperature deviations TA (Panel A); and lowest value of deviation of temperature variability TAV (Panel B). We group the middle three quintile portfolios together by equal-weighting their respective returns and denote it as "Quintiles 2–4". We report the mean excess returns, alphas based on CAPM, three-factor model, and four-factor model. "(1–5)" reports the return spread between the top and bottom quintiles.

Table 3: The effect of TA(A) and TAV(B) on industry returns

Panel A: Temperature anomalies: TA

	Ind	Energy	Health	IT	Utilities	Staple	C. Disc	Mat	Fin	Comm
TA	0.0510	0.1452	0.0852	-0.0076	-0.1004**	-0.0036	-0.0268	-0.0780	0.0119	-0.0101
	(1.1508)	(0.9032)	(0.8592)	(-0.1381)	(-2.5604)	(-0.0500)	(-0.5041)	(-1.0290)	(0.3195)	(-0.1021)
LOGSIZE	-4.3981***	-2.7935***	-4.0251***	-4.5562***	-3.1566***	-4.6041***	-5.1566***	-5.7560***	-2.8803***	-4.4655***
	(-11.816)	(-5.6288)	(-8.2804)	(-9.5827)	(-7.0067)	(-8.3714)	(-14.519)	(-12.504)	(-11.977)	(-7.3882)
B/M	0.0042	-0.0456*	-0.0224	0.0447*	0.0349	0.0355	0.0269	0.1293***	-0.0177*	0.0552**
	(0.2098)	(-1.9141)	(-1.1148)	(1.7702)	(1.5437)	(1.5955)	(1.1453)	(4.6954)	(-1.7409)	(2.0166)
ROE	0.0360***	0.0181	0.0351***	0.0517***	0.0619***	0.0486***	0.0516***	0.0706***	0.0795***	0.0345***
	(4.1566)	(1.1995)	(4.4550)	(6.9696)	(2.8095)	(3.2003)	(8.2675)	(6.9395)	(6.4879)	(3.5929)
LEVERAGE	0.0014	-0.0255	-0.0001	0.0361***	-0.0033	0.0180	-0.0420***	0.0152	-0.0213**	0.0223
	(0.1429)	(-1.2480)	(-0.2092)	(2.6880)	(-0.1727)	(1.2436)	(-2.8260)	(0.9949)	(-2.2622)	(1.0244)
INVEST/A	0.0501*	0.0913	0.0618	0.0439	0.0126	0.1058*	-0.0246	0.0025	-0.1464*	-0.0403
	(1.6797)	(1.5282)	(1.1325)	(0.6122)	(0.3603)	(1.9201)	(-0.8990)	(0.0481)	(-1.8887)	(-0.6033)
LOGPPE	0.9937***	1.7880*	-0.3065	-0.0303	0.1252**	0.9673***	0.8023***	0.7069*	0.4224**	0.9395**
	(3.7276)	(1.8732)	(-0.8975)	(-0.0955)	(2.3325)	(3.7254)	(2.6222)	(1.7622)	(2.2345)	(2.4444)
MOM	0.0235	-0.1375	-0.0134	-0.0499	-0.0545	0.0437	-0.0692*	0.0504	-0.2512***	-0.1031
	(0.5090)	(-1.2486)	(-0.2569)	(-1.1200)	(-0.5840)	(0.6600)	(-1.6582)	(0.8254)	(-5.3834)	(-1.2196)
Year/month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	26670	6731	17509	18058	6321	7441	18543	8911	22365	5380
Firm/year cluster	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0237	0.0239	0.0138	0.0294	0.0210	0.0278	0.0355	0.0406	0.0279	0.0314

Panel B: Temperature anomaly variability: TAV

	Ind	Energy	Health	IT	Utilities	Staple	C. Disc	Mat	Fin	Comm
TAV	-0.2476	-0.9477**	0.4770	0.2354	0.3552**	-0.9432***	-0.6084***	0.0163	-0.0670	0.5953
	(0.1541)	(0.4652)	(0.3478)	(0.2283)	(0.1538)	(0.2646)	(0.2236)	(0.2770)	(0.1357)	(0.4177)
LOGSIZE	-4.3964***	-2.7972***	-4.0210***	-4.5571***	-3.1496***	-4.6158***	-5.1595***	-5.7561***	-2.8808***	-4.4402***
	(0.3723)	(0.4961)	(0.4868)	(0.4755)	(0.4501)	(0.5489)	(0.3551)	(0.4605)	(0.2404)	(0.6057)
B/M	0.0042	-0.0459*	-0.0232	0.0451*	0.0360	0.0353	0.0278	0.1289***	-0.0177*	0.0536*
	(0.0200)	(0.0238)	(0.0201)	(0.0253)	(0.0226)	(0.0222)	(0.0235)	(0.0275)	(0.0102)	(0.0275)
ROE	0.0359***	0.0179	0.0350***	0.0518***	0.0616***	0.0486***	0.0516***	0.0705***	0.0794***	0.0347***
	(0.0087)	(0.0150)	(0.0079)	(0.0074)	(0.0220)	(0.0152)	(0.0062)	(0.0102)	(0.0123)	(0.0096)
LEVERAGE	0.0012	-0.0261	-0.0001	0.0362***	-0.0043	0.0179	-0.0417***	0.0148	-0.0213**	0.0221
	(0.0097)	(0.0204)	(0.0006)	(0.0134)	(0.0189)	(0.0145)	(0.0149)	(0.0153)	(0.0094)	(0.0218)
INVEST/A	0.0502*	0.0922	0.0575	0.0441	0.0134	0.1048*	-0.0245	0.0032	-0.1464*	-0.0430
	(0.0298)	(0.0596)	(0.0547)	(0.0717)	(0.0351)	(0.0550)	(0.0273)	(0.0515)	(0.0776)	(0.0668)
LOGPPE	0.9949***	1.8210*	-0.3006	-0.0319	0.1170**	0.9734***	0.7981***	0.7175*	0.4214**	0.9523**
	(0.2666)	(0.9533)	(0.3400)	(0.3172)	(0.0536)	(0.2603)	(0.3062)	(0.4015)	(0.1890)	(0.3845)
MOM	0.0237	-0.1369	-0.0135	-0.0502	-0.0561	0.0468	-0.0698*	0.0516	-0.2513***	-0.1056
	(0.0460)	(0.1104)	(0.0521)	(0.0446)	(0.0932)	(0.0662)	(0.0417)	(0.0611)	(0.0467)	(0.0843)
Year/month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	26670	6731	17509	18058	6321	7441	18543	8911	22365	5380
Firm/year clusters	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.0237	0.0243	0.0139	0.0295	0.0209	0.0295	0.0359	0.0405	0.0279	0.0317

Standard errors reported in parentheses
***1% significance,**5% significance, *10% significance,

Table (3). The sample period is 2005-2020. All variables are defined in Tables (1) in the Data section. The independent variables include the deviation of daily temperature from its historical mean within a month (Panel A) or the deviation of daily temperature variability from its historical variability level within a month (Panel B). We use the Global Industry Classification Standard to identify a firm's sectoral affiliation. We consider the following sectors: Information Technology (IT), Health Care (Health), Financials (Fin), Consumer Discretionary (C. Disc), Communication Services (Comm), Industrials (Ind), Consumer Staples (Staple), Energy, Utilities, Real Estate (RE), and Materials (Mat). We refer to this document for an overview of the classification: `http://www.msci.com/our-solutions/indexes/gics`. We report the results of the panel regression with standard errors clustered at the firm and year levels. All regressions include month fixed effects and firm fixed effects.

Table 4: Estimation for TA and TAV, three sector, different periods

	Energy			Staple			Health		
Dep. Variable: r	2006-2010	2011-2015	2016-2020	2006-2010	2011-2015	2016-2020	2006-2010	2011-2015	2016-2020
$\widetilde{TD}$	0.267	0.1491	0.180	-0.324	-0.0739	0.3745	0.4770	0.1546	0.1036
	(0.4652)	(0.5246)	(0.7636)	(0.2646)	(0.2898)	(0.4061)	(0.3478)	(0.3990)	(0.5384)
TD-VAR	-0.4975*	-0.0863	-2.4626***	-1.0146***	-0.9042***	-0.8223***	0.4770	0.3278	0.5901
	(0.3652)	(0.5246)	(0.7636)	(0.2646)	(0.2898)	(0.4061)	(0.3478)	(0.3990)	(0.5384)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	6731	5171	3067	7441	5523	3252	17509	13700	9017
Cov. Est.	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R-squared	0.0243	0.0386	0.0621	0.0295	0.0260	0.0478	0.0139	0.0127	0.0161

Standard errors reported in parentheses
***1% significance,**5% significance, *10% significance,

Table 4 The sample period 2005-2020 is divided into three equal sub-periods. The independent variables include in turn the deviation of daily temperature from its historical mean within a month (first row) or the deviation of daily temperature variability from its historical mean in the same month (second row). We report the results of the panel regression with standard errors clustered at the firm and year levels. All regressions include month fixed effects and firm fixed effects

Table 5: The impact of TA and TAV on state-specific climate attention

	Climate Change (a)			Climate Variability and Change (b)		
	(1)	(2)	(3)	(4)	(5)	(6)
TAV	3.171***	3.376***	0.773**	0.672**	0.716**	0.239
	(6.42)	(6.57)	(2.25)	(2.04)	(2.01)	(0.65)
TA	-0.400***	-0.380***	-0.077	-0.063	-0.058	-0.167
	(-3.64)	(-3.40)	(-0.70)	(-0.62)	(-0.57)	(-1.11)
State FE	No	Yes	Yes	No	Yes	Yes
YearxQuarter FE	No	No	Yes	No	No	Yes
R Squared	0.018	0.019	0.742	0.002	0.002	0.088
Observations	2950	2950	2950	2950	2950	2950

This table presents results associating state level Google attention to the topics "Climate Change" and "Climate Variability and Change" to temperature anomalies (TA) and variability of temperature anomalies (TAV). The two attention indices, at the quarterly frequency, are regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 6: The impact of TA and TAV on national climate attention

	(1)	(2)	(3)
TAV	0.932**	1.077**	0.677
	(2.435)	(2.306)	(1.382)
TA	-0.204	-0.220	-0.101
	(-0.882)	(-1.051)	(-0.538)
Fixed Effect	None	Quarter	Yr Quarter
R Squared	0.089	0.247	0.507
Observations	50	50	50

This table presents results associating the national Wall Street Journal news index developed by Engle et al. (2020) to temperature anomalies (TA) and variability of temperature anomalies (TAV). The attention index, at the quarterly frequency, is regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 7: The impact of TA and TAV on the attention paid by earnings call participants to physical risk

	Full Sample			Concentrated Firms		
	(1)	(2)	(3)	(4)	(5)	(6)
TAV	4.312**	5.299***	5.275***	2.586*	2.854*	2.800*
	(2.683)	(2.966)	(2.970)	(1.784)	(1.969)	(1.991)
TA	-0.622	-0.108	-0.271	0.157	0.661	0.480
	(-0.712)	(-0.155)	(-0.375)	(0.293)	(1.305)	(0.918)
WSJ Innovation		0.394	2.031**		0.304	2.162*
		(0.563)	(2.166)		(0.342)	(1.771)
WSJ			-1038.260**			-1172.748**
			(-2.344)			(-2.188)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R Squared	Yes	Yes	Yes	Yes	Yes	Yes
Observations	0.068	0.057	0.057	0.025	0.055	0.055
obs	20583	17076	17076	15059	12470	12470

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table presents results associating the physical climate exposure attention index developed by Sautner et al. (2023) to temperature anomalies (TA) and variability of temperature anomalies (TAV). The yearly innovations in the attention index is regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 8: The impact of TA and TAV on firm revenue

Panel A: Total Revenues

	(1) All Industries	(2) Cons Disc/Staples	(3) Utilities	(4) Energy
TAV	-0.149	-0.011**	0.001	-0.335*
	(-1.239)	(-2.488)	(0.741)	(-2.197)
TA	0.039	0.001	-0.001	-0.046
	(0.958)	(0.634)	(-1.531)	(-1.397)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
R Squared	0.023	0.728	0.650	0.142
Observations	61066	8415	2914	3178

Panel B: Sales

	(1) All Industries	(2) Cons Disc/Staples	(3) Utilities	(4) Energy
TAV	-0.124	-0.011**	0.001	-0.335*
	(-1.234)	(-2.488)	(0.741)	(-2.197)
TA	0.034	0.001	-0.001	-0.046
	(0.963)	(0.634)	(-1.531)	(-1.397)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
R Squared	0.023	0.728	0.650	0.142
Observations	70201	8415	2914	3178

This table presents results associating firm revenues and sales to temperature anomalies (TA) and variability of temperature anomalies (TAV). Both total revenues and sales are scaled by the year ago total assets of the firm. The scaled variables are regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 9: The impact of TA and TAV on firm expenses

Panel A: Total Operating Expense

	(1) All Industries	(2) Cons Disc/Staples	(3) Utilities	(4) Energy
TDVAR	-0.075	-0.008**	0.000	-0.252*
	(-1.145)	(-2.060)	(0.355)	(-2.171)
TD	0.022	-0.000	-0.000	-0.033
	(1.024)	(-0.102)	(-0.644)	(-1.207)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
R Squared	0.026	0.746	0.682	0.181
Observations	70076	8401	2913	3164

Panel B: Cost of Goods Sold

	(1) All Industries	(2) Cons Disc/Staples	(3) Utilities	(4) Energy
TAV	-0.078	-0.006**	0.000	-0.228**
	(-1.268)	(-2.140)	(0.331)	(-2.285)
TA	0.020	-0.000	-0.000	-0.037
	(0.913)	(-0.015)	(-0.642)	(-1.475)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No
R Squared	0.024	0.783	0.685	0.147
Observations	70115	8410	2913	3168

This table presents results associating firm expenses and cost of goods sold to temperature anomalies (TA) and variability of temperature anomalies (TAV). Both total revenues and sales are scaled by the year ago total assets of the firm. The scaled variables are regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 10: The impact of TA and TAV on gross plant, property, equipment

	(1) All Industries	(2) Cons Disc/Staples	(3) Utilities	(4) Energy
TAV	-0.009***	-0.012*	0.009	-0.002
	(-3.041)	(-1.811)	(1.505)	(-0.080)
TA	0.001	0.004	0.001	-0.004
	(0.642)	(1.382)	(0.395)	(-0.233)
Firm FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	No	No
R Squared	0.794	0.820	0.663	0.597
Observations	39810	5301	2646	2709

This table presents results associating firm gross plant, property and equipment to temperature anomalies (TA) and variability of temperature anomalies (TAV). Both total revenues and sales are scaled by the year ago total assets of the firm. The scaled variables are regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 11: Reporting TAV: Firm level exposure

State	**TAV**	**Installations**
AZ	-0.18	3
CA	0.77	5
CO	-1.87	2
IA	-1.23	4

Firm Exposure	
High	36%
Medium	21%
Low	43%

Table(11). Shows a practical approach for climate reporting exercise from a firm point of view. The first part reports the firm's installation breakdown among the 4 states in which it operates. Associated to each state, TAV indicates the magnitude of TAV forecasted for the following operating period. The last section of the table presents the percentage of firm's installations that are exposed respectively at a high, medium or low TAV risk.)

Table 12: Reporting TAV: Portfolio Exposure

State	Pct Portafoglio	TAV
NV	8.81%	-0.01
OK	29.88%	-0.53
OR	23.28%	1.19
SD	38.03%	-0.25
TAV Exposure		0.024

Table(12). Shows a practical approach for climate reporting exercise for a hypothetical Financial Portfolio. The first column reports the different states in which stock headquarters are located. The second column reports the Percentage of portfolio allocation invested in firms whose headquarters correspond to the state. The column TAV reports the forecasted TAV for the following year. TAV exposure represents the weighted average of TAV exposure.)

Table 14: Estimation of Weather Derivates price driver

	CDD		HDD	
	(1)	(2)	(1)	(2)
T_m	22.262***	25.516***	-25.980***	-26.018***
	(1.7786)	(2.1067)	(0.8380)	(0.9349)
TAV		4.0458**		3.5812***
		(1.9917)		(0.8282)
TA		-11.082***		5.4309***
		(1.6592)		(0.6308)
$\sigma(TA)$		2.0248		19.595**
		(6.0450)		(9.2184)
α			326.87***	140.60*
			(11.508)	(79.420)
Estimator	PanelOLS	PanelOLS	PanelOLS	PanelOLS
No. Observations	438	438	542	542
Cov. Est.	Clustered	Clustered	Clustered	Clustered
R-squared	0.8807	0.9188	0.9501	0.9630

Standard errors reported in parentheses
***1% significance,**5% significance, *10% significance,

Table 14. Sample period is 2015-2020. Estimation of model 12 for different specification. The dependent variabile is CDD and HDD respectively and the main independent variable is T_m that represent the maximum temperature minus 65°F, threshold level for futures contract traded at CME. Model (1) considers only T_m as regressor, that represent the underlying. (2) considers all the regresses.Estimation is run trough a PanelOLS employing fixed effect for entities and time. Standard errors are clustered both at entity and time levels

Table 15: Estimation Results for energy consumption

	Residential	Commercial	Industrial	Total
$TD\text{-}VAR$	0.0054***	0.0006	0.0020**	0.0025***
	(0.0011)	(0.0006)	(0.0009)	(0.0005)
$\widetilde{TD}$	-0.0011	0.0013**	0.0004	0.0002
	(0.0008)	(0.0006)	(0.0004)	(0.0006)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
No. Observations	9000	9000	9000	9000
Cov. Est.	Clustered	Clustered	Clustered	Clustered
R-squared	0.0038	0.0034	0.0010	0.0027

Standard errors reported in parentheses

***1% significance,**5% significance, *10% significance,

Table (15) The sample period is 2005-2020. The Table presents the estimated coefficient for equation $\epsilon_t = \beta_v * TDVAR + \beta_t * TD + \gamma_t + \eta_n + \epsilon$ in the different sectors, Residential, Commercial, Industrial and Total, that represents the aggregation. Estimation is run trough a PanelOLS employing fixed effect for entities and time. Standard errors are clustered both at entity and time levels. The sample period is 2005-2020 for the 50 US state. $\widetilde{TD}$ and $TD\text{-}VAR$ are the state level temperature measure as defined in equation (**??**, 5)

Table 16: The impact of TA and TAV on retail sales

	(1)	(2)	(3)	(4)	(5)
TA	0.094		0.011		-0.002
	(1.621)		(0.152)		(-0.029)
TAV		-2.259***		-1.969**	-1.970**
		(-6.962)		(-3.026)	(-2.901)
Time FE	No	No	Yes	Yes	Yes
Adj R Squared	0.009	0.095	0.259	0.295	0.295
Observations	396	396	396	396	396

This table presents results associating year-over-year growth in retail sales for the largest metropolitan areas in the US to temperature anomalies (TA) and variability of temperature anomalies (TAV). Both total revenues and sales are scaled by the year ago total assets of the firm. The scaled variables are regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T statistics in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

11 Figures

Figure 1: Distribution of Temperature Anomalies in the US

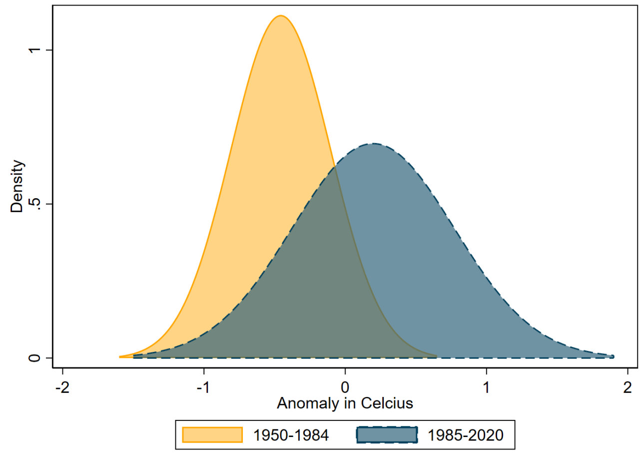
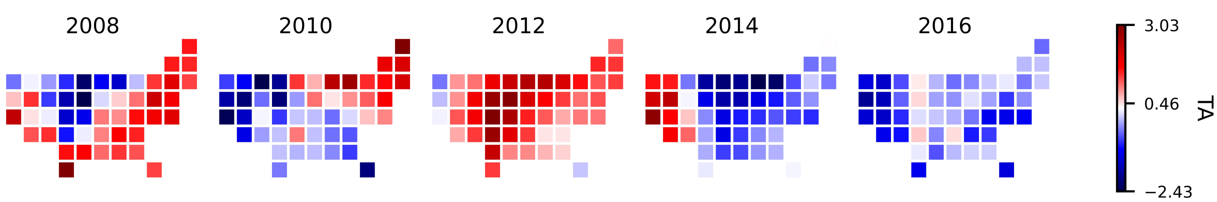


Figure 1 illustrates the normal density distribution of average yearly temperature anomalies for 35-year periods in the United States. Data is collected from the Berkeley Earth Land Temperature Record that defines an anomaly as the realized temperature subtracted from the average in the pre-industrial period, 1850-1900.

Figure 2: Geographic Variation in Temperature Statistics

(a) Yearly TA



(b) Yearly TAV

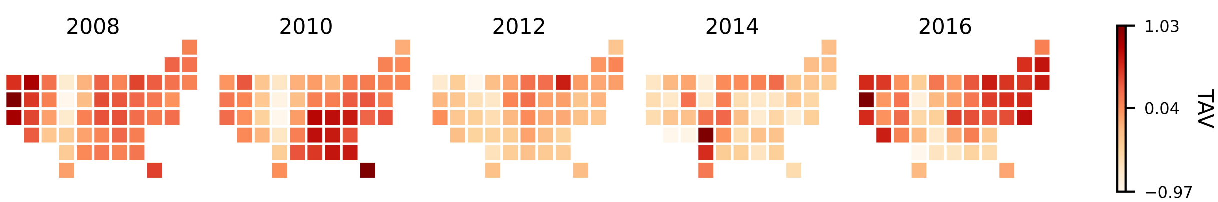
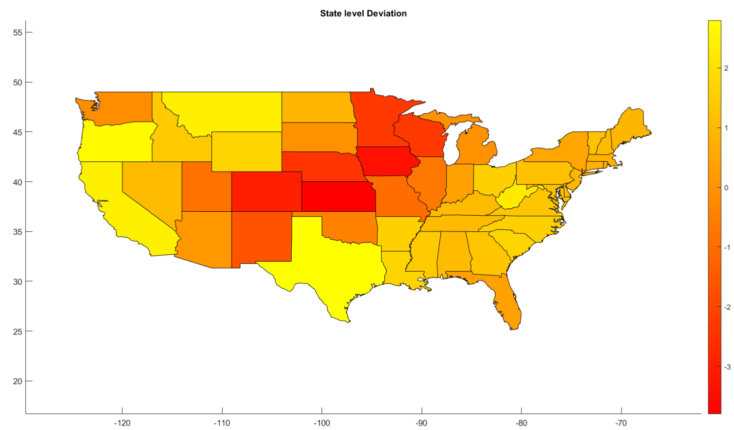
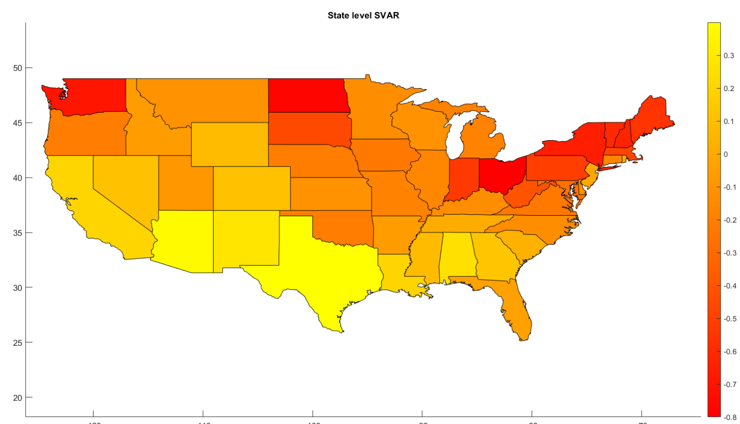


Figure 2 shows yearly TA and TAV for states in the contiguous US in graphs A and B, respectively. The base period for calculating the metrics is 1960-2005. For graph A, blue regions are colder than the base period while red regions are hotter. For graph B, light regions have lower variability than the base period while darker red represents higher variability.

Figure 3: TA and TAV in US in September 2015





The two panels show the different temperature metrics at the state level across the U.S. for September 2015. Panel A displays the temperature anomaly (TA) for each state, while Panel B highlights the variability in temperature anomaly (TAV). In the heatmap, states with higher exposure are colored in yellow, whereas those with lower exposure are represented in red

Figure 4: TA and TAV in New Mexico and Alabama

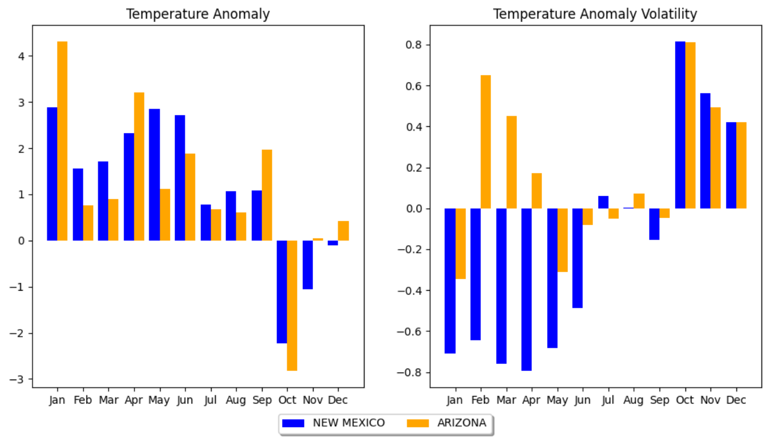
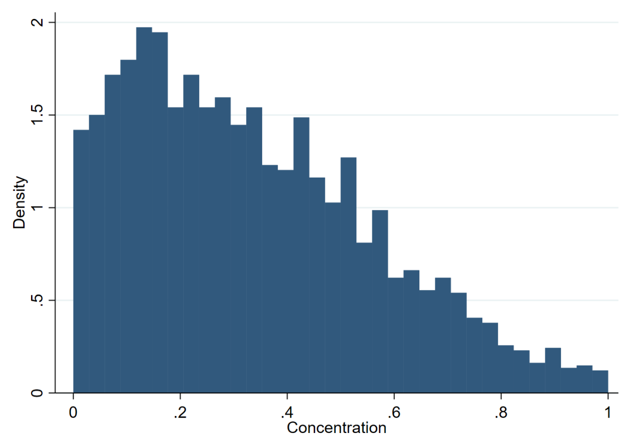


Figure 4 shows for 2017, the left panel depicts the Temperature Anomaly (TA) for New Mexico (in blue) and Arizona (in yellow), while the right panel illustrates the Temperature Anomaly Variability (TAV) for the same states. Bars above the zero line indicate temperatures above the historical average, while those below show temperatures that were lower. Despite both states presenting analogous temperature anomalies, Arizona exhibited a higher variability, suggesting more pronounced fluctuations and potential for extreme temperatures.

Figure 5: Geographic concentration of firms in the Russell 3000 based on 10-Ks



This histogram represents the geographic concentration of each firm in the Russell-3000 using the methodology outlined in Garcia and Norli (2012) and Bernile et al. (2015). Specifically, we use a 10-K-based measure of firm local exposure. We parse the 10-K filings of all Russell-3000 firms for each year to identify the number of times the U.S. states and Washington DC are mentioned in sections 1A, 2, 6, and 7. The firm-headquarter citation count is calculated by dividing the total number of mentions of the headquartered state by the total mentions of all U.S. states and Washington DC. Finally, we average this for each firm to obtain a metric which we define as the 10-K measure of state operational dispersion. If the average number of mentions is closer to one then the firm only mentions their headquartered state and vise versa.

Figure 6: Unadjusted long-short returns of portfolios sorted on TA and TAV

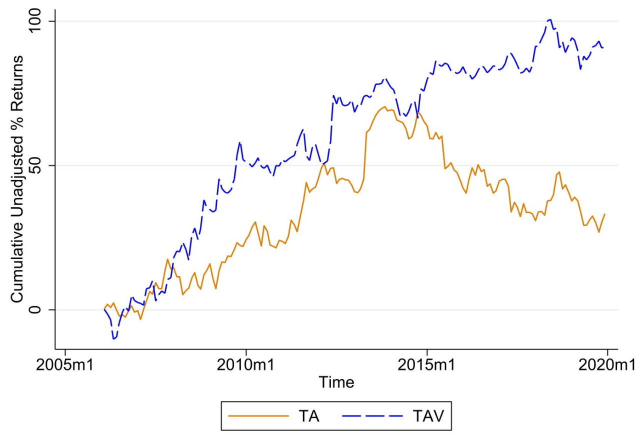


Figure 6 presents the long-short portfolio returns sorted either on US state exposure to temperature anomalies (TA) or volatility of temperature anomalies (TAV). The long-short portfolio methodology consists of sorting 40 states into exposure quartiles for a given month, i.e., the top ten most exposed states to either TA or TAV in a given month are assigned to the short portfolio and vise versa. We remove 10 states based on the lack of firms headquartered there. We calculate the average value-weighted returns of firms headquartered in the states assigned to each of the four exposure portfolios. Each line is therefore the monthly difference between the average return in the most versus lease vulnerable portfolio based on either TA or TAV.

A Appendix A

B Alternative construction of temperature variables

In the main text, we detail the construction of $T_{s,[d,m,y]}$, where it represents an equally weighted average of the temperature attributed to each grid cell within state s. Using an equal weighting approach might overlook certain crucial aspects. This can be illustrated by evaluating the US-wide temperature metrics, where each state is perceived as a distinct cell. The challenge, when aggregating at the national level, is determining the appropriate weighting. Using an equal weight implies that a pronounced TAV in a smaller state would have the same impact on the final index as a similar TAV in a larger state. Consequently, the selected weighting mechanism should reflect the relative importance of each state within the broader national context.

Two logical choices emerge: GDP-based and population-based weights. Given that neither measure is available monthly (with GDP being quarterly and population yearly), we forward-fill the data to derive monthly series compatible with TA and TAV. Using GDP weights emphasizes the relative importance of economically productive regions, translating to a specific economic impact of TA and TAV. On the other hand, population-based weights prioritize human experiences: greater variability in a densely populated state holds more significance than in a sparsely populated one.

Figure 7 contrasts the U.S.-wide TAV index based on different weighting criteria. A comparison of the three measures reveals minor differences, particularly when juxtaposing equal weighting against population or GDP-based weights.

Figure 7: TAV and weighting method

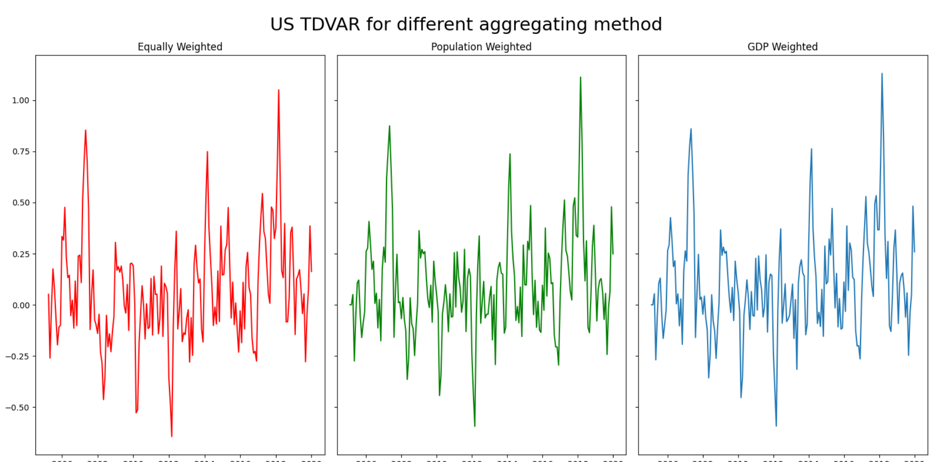


Figure 7 displays three primary index constructions for the period 2005-2020, each based on a distinct weighting method for TAV for the US. The left panel illustrates an equi-weighted index construction, where $W_i = 1/N_i$ with $N_i = 50$. The central panel employs a population-based weighting method, defined as $w_i = pop_{i,t}/\sum_i pop_{i,t}$. The right panel presents the US-wide index using state GDP as the weight, formulated as $w_i = \dfrac{GDP_{i,t}}{\sum_i GDP_{i,t}}$