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

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Abstract

We establish the financial materiality of temperature variability by demonstrating its impact on US firms and investors. A long-short strategy that sorts firms based on exposure earns a market-adjusted alpha of 39 basis points per month. This variability metric is related to aggregate decreases in firm profitability, with asymmetric effects across industries. These outcomes are driven by reductions in consumer demand and labor productivity coupled with changes in media and investor attention. The geographically scalable statistical framework provides a reference for assessing the quantitative effects of climate-related physical risks, offering a metric for improving the disclosure of material climate risks.

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

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

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1 Introduction

Climate change is disrupting temperature and weather patterns, causing temperature anomalies. Meanwhile, agencies like the Securities and Exchange Commission (SEC) and the European Financial Reporting Advisory Group, along with investors (Ilhan et al., 2023), are demanding corporate disclosure of material climate-related physical risks, such as changes in temperature.[1] This is, however, undermined by a lack of quantitative metrics that meet the conservative legal threshold of materiality: that which affects the economic value of a company and influences the decisions of a reasonable investor (Katz and McIntosh, 2021). Instead, the climate-related information disclosed by firms is largely qualitative and uninformative for investors (Christensen et al., 2018), who have the costly task of wading through corporate filings, sifting for relevant signals.[2]

This paper addresses this informational inadequacy by examining two statistics—changes in the mean and changes in the standard deviation of temperature anomalies—that can serve as metrics to evaluate the impact of climate-induced temperature changes on firms and investors. Our statistical tests demonstrate that these metrics incorporate the properties of disparate indicators previously used to understand the economic and financial implications of temperature changes.[3] However, we argue that temperature variability—measured by the changes in the standard deviation with respect to a historical baseline—is materially relevant for both firms and investors. This is because variability, more than changes in the mean, represents the increasing frequency and intensity of temperature variations and, at the same time, captures changes across the entire distribution of anomalies. We find empirical evidence supporting our claim, showing that returns and profitability primarily respond to variability, rather than changes in the mean, driven by factors such as lower consumer demand, reduced productivity across industry sectors, and heightened investor and media attention.

Our identification strategy relies on isolating the differential spatial exposure of firms

[1]Although the SEC's disclosure rules are on hold due to legal issues, California has enacted the Climate-Related Financial Risk Act in July 2023, which applies to around 10,000 companies.

[2]See Loughran and McDonald (2014) and Cohen et al. (2020) regarding disclosure length and complexity.

[3]Many studies investigate the impacts of average temperature (Dell et al. (2012); Hsiang et al. (2017); Barreca et al. (2016)) and anomalies (Carleton and Hsiang, 2016) on macroeconomic indicators. The finance literature has also evaluated the effects of the number of days above 30°C (Pankratz et al. (2023);Addoum et al. (2020)), above 100°F (Acharya et al., 2022), and absolute temperatures in general (Addoum et al., 2023)).

to the two temperature metrics. We formulate these metrics using maximum surface temperature data at a 1-by-1-degree grid level, and their aggregation to the state level reveals distinct spatial and temporal variations, shown in Figure 1. This setting allows us to test the effects of two arguably exogenous temperature shocks ((Auffhammer et al., 2013); (Dell et al., 2014)) on firms over time and space. We match firms to their headquartered states, expecting that operations primarily occur near that state. As this is a strong assumption, we use two restrictions: (i) excluding firms that frequently reference multiple states other than their headquarter state, following the approach of Garcia and Norli (2012), and (ii) removing firms with a substantial proportion of foreign revenue.

Our empirical tests begin by implementing a geographic long-short portfolio strategy, using Russell 3000 firms, to examine the impact of state-level exposure to each temperature metric on returns from 2005 to 2019. A monthly strategy that goes long on firms operating in states least affected, and short on firms in states most affected by variability, yields an average factor-adjusted return of 4.68% per year. Excess returns increase by 58 basis points when narrowing the sample to firms with a greater proportion of their revenues and operations within the US. In contrast, using the same strategy with changes in the mean yields insignificant returns of 0.24% per year for firms in the least impacted states. To the extent that temperature anomalies may be representative of other changing weather phenomena, we include precipitation as an additional sorting feature and find that our results remain robust.[4] This finding highlights a key contribution: equities are responsive to shifts in temperature variability, but show no reaction to changes in the mean.

These results raise the question of whether the return reaction results directly from operational impacts, or whether it stems from heightened investor attention and a shift in climate beliefs. The existing literature on investor attentiveness to climate shocks is ambigu-

[4] We recognize that climate change is amplifying other weather phenomena beyond temperature variability, such as precipitation extremes and droughts, however, there is theoretical and empirical support for focusing on temperature variability. Temperature changes are linked with other weather phenomena. For instance, research has shown that temperature extremes can influence precipitation patterns and drought. Box 11.1 of the IPCC's 6th Assessment Report provides an overview of the relationship between temperature, precipitation extremes, and droughts, highlighting the interconnectedness of these climate phenomena. Moreover, empirical evidence suggests that temperature variability has a distinct impact, even when controlling for other weather extremes. Studies have shown that regardless of whether precipitation extremes are included in the analysis, temperature variability consistently exhibits an independent effect Kotz et al. (2021).

ous. For instance, Hong et al. (2020) and Addoum et al. (2023) report an underreaction to droughts and temperature, while Choi et al. (2020) finds the opposite for heatwaves.[5] We disentangle these two mechanisms by finding evidence aligned with both perspectives.

First, to assess the effects of temperature anomalies on firms' operating performance, we analyze how the two indicators influence profitability. We find significant decreases in profitability—measured by return-on-assets—with greater temperature variability in the construction, finance, and healthcare industries. Similarly, the business equipment, durables, and transportation industries show negative responses to variability. Conversely, the utilities and energy industries see increased profitability with higher variability. Across all industries, a one-standard-deviation rise in quarterly variability decreases profitability of the average firm by 0.42 basis points—a relative decrease of 2.58% compared to the sample mean. Utilities are the only sector negatively impacted by the mean.

We explain these effects as disruptions in consumption and labor productivity caused by the tangible effects of severe temperatures, such as excessively hot or cold days (Starr (2000); Graff Zivin and Neidell (2014); Neidell et al. (2021)). Using granular household expenditure data from the US Consumer Expenditure Survey, we find that a one-standard-deviation increase in variability reduces household spending by US$134 per year. The economic impact is therefore substantial when extrapolated to a state or to the entire country. Substantiating our profitability results, we observe a heterogeneous impact on expenditure: spending on non-durables, durables, and apparel decreases with variability, while utility spending increases.

Furthermore, temperature variability appears to concomitantly affect labor productivity. Using data from the US Census Bureau, we demonstrate that a one-standard-deviation increase in the variability metric reduces time spent working by three minutes per worker per week, averaged across all industries. The effects are more pronounced in construction, durables, and hospitality, which experience reductions of eight, five, and four minutes per week, respectively. Data from the American Time Use Survey corroborate these findings, indicating three minutes lost in weekly time worked for individuals employed in temperature-sensitive industries. These results align with Neidell et al. (2021), who find that workers in

[5] See also, Egan and Mullin (2012), Deryugina (2013), Joireman et al. (2010), Fownes and Allred (2019), Sisco et al. (2017).

high-risk industries experience a decrease of 2.6 minutes in work time during a 90°F day.

Second, to investigate the effect of temperature on firms via changes in investor attention, we aggregate the temperature metrics at both state and national levels and obtain innovations in Google Search Volume for the topic "Climate Change". Our findings reveal a significant relationship between variability and the topic, indicating elevated attention. Leveraging the news index from Engle et al. (2020), which measures US media coverage of climate change tailored to investors, we observe an association between unexpected news and variability, but no association with the mean. To further validate this channel, we examine whether sell-side analysts probe firms that experience temperature shocks, using an earnings-call attention measure from Sautner et al. (2023). This measure shows a positive correlation with all firms, even when controlling for other news indices. These findings underscore the importance of temperature variability, suggesting that shocks in this measure act as a "wake-up call", prompting a shift in prices through a behavioral attention channel.

A rationale for the observed return reaction is that investors' attention is a limited resource (Van Nieuwerburgh and Veldkamp, 2010) which can be redirected when unusual weather events occur, altering the equilibrium price of an asset. Many papers rely on these attention shocks—either through direct temperature effects (see Choi et al. (2020) or Alekseev et al. (2021)) or through media coverage (Engle et al., 2020), which is plausibly influenced by unusual weather—to understand how trading behavior changes as a result of climate risks.[6] However, there is evidence that the broader public is becoming inured to unusual temperatures through repeated exposure (Moore et al., 2019). Our findings show that certain characterizations of the temperature anomaly distribution are ineffective in changing the behavior of investors and, ultimately, asset prices. In line with this phenomenon of social normalization to temperatures, our statistical analysis reveals that changes in the mean are progressively less effective at capturing changes in the temperature distribution over time. Moreover, we find that sophisticated investors react to firm-specific exposure to temperatures, even while controlling for climate news coverage and attention.

Evidence using the variability metric highlights that changes in temperature, as climate-

[6] Physical risks can be considered a driver of media attention. Faccini et al. (2023), for example, attribute climate risks such as record-breaking temperatures and floods to news articles from Refinitiv.

induced phenomena, represent a critical physical risk with material relevance for firms and investors across multiple sectors. These findings have implications for policymakers and investors, given the increased global demand for consistent and comparable climate risk disclosure (Carattini et al., 2022). We illustrate the value of the variability metric in both the reporting and forward-looking measurement of temperature risk. First, we show how firms can use the metric to report their exposure to future temperature risk, informing financial markets about their vulnerability to climate-related temperature shocks in the future. Second, we show how it can help investors evaluate the exposure of companies within their portfolios over a relevant future time horizon and adjust their allocation to minimize portfolio exposure.

This study contributes to the financial literature on climate change by: (i) establishing the financial materiality of temperature variability, (ii) linking this variability to its financial impacts on firms and investors, and (iii) identifying the channels through which these effects are manifested. Related studies (Bansal et al. (2017); Addoum et al. (2020);Pankratz et al. (2023); Acharya et al. (2022)) examine the effects of temperature on financial markets based on predetermined thresholds or the right tail of the distribution. Our statistics represent many of these attributes; however, the market appears to be myopic to some implications of the changing distribution, perhaps accounting for the mixed results of the previous research.

The construction of the variability metric using the distribution of temperature anomalies, and its documented broad effects on returns, income, consumption, and production, significantly differentiates our work from Addoum et al. (2023). Their study uses the distribution of *absolute* temperatures to show seasonal industry-specific effects on profitability, yet they find no immediate impact on equities and observe no investor reaction.[7] Our approach, by contrast, centers on the portfolio response to temperature, identifying investor attention, consumer behavior, and labor productivity as the main channels of influence. Using the distribution of temperature anomalies, rather than absolute temperatures, allows us to isolate the effects of random variation in weather as well as the additional perturbations resulting from climate change. This application of anomalous temperatures may help to explain why

[7] Addoum et al. (2023) additionally classify temperature exposure relative to the historical mean number of hours spent above 30°C.

investors seem increasingly indifferent to extreme absolute temperatures over time (Moore et al., 2019) and why income effects in Addoum et al. (2023) are only observed in specific seasons for certain industries.

Several papers investigate the link between temperature and investor responses. Choi et al. (2020) finds that local temperature shocks can heighten investors' attention, affecting the cross-section of returns. Alekseev et al. (2021), with a similar argument, finds that mutual funds respond by shifting their portfolio allocation. Schlenker and Taylor (2021) demonstrate that participants in weather markets revise their expectations by incorporating warming trends. Our use of the variability metric uniquely reveals that deviations in temperature variability trigger a spatially specific attention shock and also indirectly impact investor attention through increased news coverage of climate change. This substantially advances the discussion on the impacts of temperature anomalies on investor beliefs and behaviors.

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 US National Oceanic and Atmosphere Administration 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. Lastly, we obtain data on population and gross domestic product (GDP) from the Federal Reserve Economic Database, released by the Federal Reserve Bank of St. Louis. Details of the data utilized in robustness checks and to validate the proposed metrics are provided in the Appendix B.

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 January 1, 1960 and ending on December 31, 2019. The BEST data are organized into a grid format, with each cell representing an area of 1 degree latitude by 1 degree longitude. A key strength of the BEST dataset is its use of over 40,000 land stations, whereas alternative datasets typically use around 10,000.[8] This extensive network enhances the accuracy of the BEST dataset, particularly when it comes to identifying record-setting daily temperatures.[9] BEST utilizes a spatial interpolation technique to ensure comprehensive and extensive spatial coverage globally, from 1960 to the present day. This means that the dataset provides a continuous and detailed record of temperature changes over several decades,[10] covering the entire globe. This is important for examining the impact of temperature on businesses operating in different countries. While this paper's analysis focuses on the United States, its methodologies and metrics can be applied to other countries or adjusted to different geographic scales. This flexibility, alongside the BEST dataset's comprehensive global coverage and detailed temperature records, allows for such adaptability and, crucially, consistent comparability across 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 to assemble state-level temperature data. However, we recognize that the significance of temperature exposure can differ based on the economic activities occurring within a particular state. Therefore, to assemble US-level temperature data from state-level data, we

[8] Contemporary literature, e.g., Choi et al. (2020), use data from PRISM which include 9,000 stations.

[9] The more stations contribute 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 dataset includes a station near the location of interest, reducing the need for interpolation between distant stations.

[10] 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).

consider state-level economies and—for robustness—populations when assigning weights to temperature values. These elements act as proxies for a state's exposure to temperature, as discussed in Colacito et al. (2019) and Natoli (2023). Specifically, we use annual data on states' economies and populations, sourced from the Federal Reserve Economic Database, released by the Federal Reserve Bank of St. Louis. The "POP" code delivers annual population values from 1950 onwards. To align these with the temperature data, we interpolate the annual frequency of the population data to produce monthly or daily series. The "RQGSP" code 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 US companies, which collectively represent about 97% of the US equity market available for investment. The constituents of the index and firm headquarters, as of 2021, are obtained from Refinitiv.

Information on the financial and accounting performance of the Russell 3000 firms is sourced from CRSP and Compustat. Table 1 presents summary statistics of various financial parameters, including earnings per share, investment rate, log book-to-market ratio, return on assets, leverage, Tobin's Q, and plant, property and equipment over total 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 annual Form 10-K filings of the Russell 3000 firms and identify the number of times a U.S. state or 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 that we define as the 10-K measure of state operational dispersion, *nearstate*. Akin to Bernile et al. (2015), we assert that our metric is a reasonable proxy to capture geographical variation in firm's activities.

Figure 2 shows the distribution of operational dispersion, where values closer to one indicate that firm activity is in the home state. The dispersion metric is right-skewed, showing that the majority of firm activity in our sample occurs in non-headquarter states. While the prior literature provides no theoretical motive for a cutoff for the metric, we remove the bottom 10% of firms using the operational dispersion (8.2%) which leaves 2,039 firms remaining in the sample. This adjustment reduces the number of firms that are least geographically concentrated in the U.S.

An additional issue is that the number of firms is heterogeneously distributed across states. Since our first empirical exercise involves constructing a long-short strategy based on sorting states by their temperature exposure, states with a minimal number of headquartered firms could distort the long-short portfolio analysis. Therefore, we remove 10 states with the fewest headquartered firms: Alaska, Hawaii, Maine, Montana, New Mexico, Wyoming, North Dakota, Vermont, South Dakota, and West Virginia. Each of these states has fewer than 14 firms headquartered within their borders. After this adjustment, combined with the operational dispersion adjustment, we are left with a sample of 2,010 firms.

Sales and operations of many US-based firms often extend beyond national borders, which can mitigate the impact of localized US temperature changes on their business. Therefore, we use Compustat segment data to discern the geographical distribution of sales among the firms in our dataset. Compustat collates this information from firms' 10-K reports. We determine the proportion of sales attributable to the US or the Americas, relative to all regions reported by the firm, averaged for the years 2005–2019 to represent the firm's spatial sales concentration over this period. Figure 3 shows the left-skewed distribution of US revenue concentration for the firms in the sample. We retain only those companies with more than 65% of their revenues originating from within the US, leaving 1,840 firms in the sample.

One limitation of using this database is its incomplete coverage of firms—Compustat notes that only 67% of North American firms disclose their geographic sales dispersion. To address the issue of missing sales data for some firms, we assumed 100% US sales for smaller firms primarily operating within their home country; larger firms with more diversified sales across regions are more likely to provide detailed geographic sales breakdowns in their 10-K reports.

2.5 Attention to climate change

We draw from three different data sources to measure market attention to climate risks for our empirical tests. We begin by extracting internet search activity data from Google Trends. We download the monthly Search Volume Index (SVI) for the search topic "climate change" for each of the 50 US states, covering 2004 (the inception of Google Trends) through to 2021. Google SVI provides a measure of interest in a particular topic by calculating the proportion of searches on that topic relative to all searches within a specific state. The state with the highest value for the topic is indexed to 100. In comparison, the remaining states are indexed proportionally from 1–100 based on their respective normalized values. We then calculate the median value of the index at the state-quarter frequency.

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. Again, we calculate the quarterly median value of the news index from the first quarter of 2005 to the second quarter of 2017. Our sample is truncated here because the index data is not available after the second quarter of 2017.

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 firms in our sample.

3 Temperature variability

Numerous studies (Dell et al. (2014) and Burke et al. (2015), among others) show that temperature has a significant impact on economic activities at the macro level. These effects are not limited to any single sector. Empirical research has demonstrated the influence of temperature anomalies (i.e. deviations of observed temperatures from historical averages) on a wide array of observable macro-economic and other outcomes, including productivity, production output, economic growth, migration, and mortality (Dell et al. (2014) and Carleton and Hsiang (2016)).[11] This focus on temperature anomalies has permeated the financial literature, with investigations targeting the extreme right tail of the temperature distribution (e.g., Addoum et al. (2020); Pankratz et al. (2023); Acharya et al. (2022)). Although there is evidence that extremely hot temperatures are already affecting various economic outcomes, such as firm earnings (Addoum et al. (2023) and Pankratz et al. (2023)), the impact of temperature changes on financial markets—particularly stocks—remains inconclusive. For instance, Addoum et al. (2023) finds that investors are generally unresponsive to extreme temperature events, whereas Acharya et al. (2022) finds that an increase in heat stress exposure is associated with higher (expected) returns. Consequently, it is difficult to definitively assert that changes in temperature—measured by extreme temperatures—have a material impact on stocks.

There is evidence that higher-order statistics—temperature variability in primis—can better represent temperature extremes (Katz and Brown, 1992) and other challenges that economic agents may face (Kotz et al., 2021). Temperature variability introduces substantial uncertainty in human behavior and markets, influencing a broad spectrum of sectors from agriculture to energy. In fact, there is evidence that variability in daily temperatures relative to seasonal and historical expectations has significant impacts on crop yields (Mendelsohn, 2007), human health (Hovdahl, 2020), sales and operational costs (Parnaudeau and Bertrand, 2018), consumer spending (Starr, 2000), macro-economic outcomes (Natoli, 2023; Alessandri

[11] Unusually hot and unusually cold temperatures can have a significant impact on agricultural productivity (Schlenker and Roberts (2009), Wheeler et al. (2000), and Ceglar et al. (2016)). Extreme temperatures might reduce hours worked and time allocated to outdoor leisure (Graff Zivin and Neidell (2014) and generate a fall in individual productivity related to heat-exposed working tasks (Cachon et al. (2012) and Somanathan et al. (2021)). Rising temperatures have also been shown to reduce economic growth (Dell et al. (2012) and Colacito et al. (2019)). This impact is particularly pronounced in developing countries (Dell et al. (2012) and Bakken and Mendelsohn (2016)). There is initial evidence that extreme temperatures could also discourage open-air activities, putting downward pressure on consumer spending through a decrease in shop retail sales (Starr (2000) and Roth Tran (2023)). Extreme temperatures can also contribute to the relocation of households from the affected area (Deryugina et al. (2018)), or even mass migration (Cruz and Rossi-Hansberg (2023)). Moreover, these extreme temperatures can have serious implications for human health and can even increase mortality rates (Deschênes and Greenstone (2011), Zanobetti and Schwartz (2008)).

and Mumta, 2022), and investor expectations (Makridis and Schloetzer, 2023; Choi et al., 2020). Temperature variability can also significantly impact businesses. Frequent changes in temperatures can disrupt production and labor schedules, increase operational costs, and affect the demand for products and services. These disruptions can, in turn, impact firm performance outcomes, leading to fluctuations in stock values. To examine this, we construct two metrics: one that captures deviations in temperature from historical averages, and another that quantifies deviations in temperature variability from past trends. The first metric consolidates the varied definitions of temperature anomalies used in existing literature, while the second—our primary focus—introduces a novel approach to quantifying changes across the entire temperature distribution. Our analysis aims to demonstrate that there is indeed a material relationship between the variability in temperature anomalies and investors' reactions, as evidenced by stock price movements, rather than by temperature anomalies alone.

In what follows, we construct the two metrics—temperature anomaly and temperature anomaly variability—and demonstrate that the second more accurately represents the frequency and intensity of temperature events, while also showing statistical superiority in capturing changes across the entire temperature distribution. By considering the changes in the shape of the distribution of temperature anomalies, including the probability of temperature extremes as indicated by the tails of the distribution, we demonstrate that this metric is a more critical determinant of materiality than is the average temperature anomaly itself.

3.1 Temperature anomaly and temperature anomaly variability

We define day-to-day temperature anomalies for a given location as deviations in the observed daily maximum temperature from its historical average:

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

where $TA_{s,[d,m,y]}$ represents our measure of daily temperature anomaly on a specific day d, in 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 maximum temperature at the same location s and on the same day d and month m, over the period 1960–2005.[12] This historical average is calculated using a window of 5 days around day d in order to smooth short-term temperature fluctuations and provide a more stable estimate of the typical temperature for that day and location. Thus, the historical average daily temperature is computed as the average of the temperatures on that specific day, as well as on the two days previous and the two days following.

We then calculate the location-specific monthly measure of day-to-day temperature anomaly by averaging the daily anomalies over the course of a given month:

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

where $D_{[m,y]}$ is the number of days in month m of year y. For convenience, we will henceforth relabel $TA := TA_{s,[m,y]}$. This calculation can easily be extended to quarterly or yearly frequencies.

Given that temperature extremes are more sensitive to changes in the variability of temperature anomalies than to changes in the mean of temperature anomalies (Katz and Brown, 1992; Schar et al., 2004), we construct a temperature variability metric to more accurately capture changes across the entire temperature probability distribution. To do that, we introduce a Temperature Anomaly Variability (TAV) index, defined as the differential between intra-month variability of temperature anomalies and a benchmark variability level. This benchmark is represented by the historical average intra-month variability of temperature anomalies, calculated over the period 1960–2005.The intra-month variability of temperature anomalies is calculated as follows:

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

where $\sigma(TA_{s,[m,y]})$ 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

[12] While $\overline{T}^{1960-2005}_{s,[d,m]}$ is a constant over the year and does not affect the time series, it does vary across location s and thus affects the cross-sectional properties of $TA_{s,[d,m,y]}$. Later, we consider a more recent cutoff year to account for potential adaptations to temperature changes.

temperature anomalies deviate from their average value for that month.

Equipped with $\sigma(TA_{s,[m,y]})$, we then calculate the TAV:

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

TAV quantifies the deviation in temperature anomaly variability from its historical average. While a positive TA indicates a month that is warmer than normal and a negative TA indicates a month that is colder than normal for a particular location, positive TAV indicates increased variability in temperature anomalies and negative TAV indicates reduced temperature anomaly variability. Positive TAV therefore means that the temperature anomaly deviations from the norm are more pronounced than usual, suggesting that location s is experiencing more frequent and intense temperature anomalies. Increased variability can lead to a higher likelihood of extreme temperature events, such as heatwaves or cold snaps, with significant impacts on various economic outcomes. To the extent that greater variability implies greater uncertainty about future temperature, and assuming that realized temperature has an effect on production or labor schedules, operational costs, or produce demand, larger temperature variability can result in increased uncertainty regarding firm performance and investment returns (Linsenmeier (2023)). Consequently, this uncertainty can impact firm valuations and stock prices. This is the primary focus of the subsequent analysis. Conversely, a negative TAV indicates reduced temperature anomaly variability, indicating more stable temperatures that are less likely to reach extreme levels. This increased predictability in temperature patterns can lead to more stable operational conditions for businesses and reduce uncertainty in firm performance and investment returns.

Our classification of temperature exposure using temperature variability distinguishes itself from the classification methods commonly used in the emerging financial literature. Most of the current financial literature focuses on extreme heat and enumerates the days or hours spent above a certain temperature threshold. These studies primarily emphasize the frequency of extreme hot temperatures. For example, Pankratz et al. (2023) and Addoum et al. (2020) use a 30°C threshold to categorize extremes, associating worker performance declines beyond this point.[13] [14] Both proposed classifications consider the frequency of extreme hot temperatures. Addoum et al. (2023) extends this by examining the effects of the distribution of absolute temperatures, considering both abnormal heat and cold, on a quarterly basis. They classify temperature exposure in two ways: first, by measuring the number of hours that the temperature exceeded 30°C; and second, by measuring the deviation from the historical mean in the number of hours that the temperature exceeded 30°C during a specific month. This second specification is close to TA.[15] Finally, to address adaptation concerns, Acharya et al. (2022) uses temperature projections to construct a heat exposure measure based on the projected number of hot days per year between 2080–2099 relative to the baseline year 2012, under the business-as-usual scenario. Again, the proposed variable measures how heat frequency is expected to increase given the future path of global carbon emissions. Therefore, all these papers focus on the frequency of extreme temperatures based on the *number of days* in a month that exceed certain thresholds. While we agree it is important to consider how often temperatures exceed thresholds, it is potentially more relevant to consider the *magnitude* of these exceedances.

Our construction of TAV aligns with Donadelli et al. (2019), but diverges in two ways. First, while Donadelli et al. (2019) uses the pre-industrial period (1659–1759) as a reference for temperature volatility, we use a more recent period. This is aligned with the decadal planning horizon of firms and the shorter horizons of investors (Bower, 1970), making it more relevant and salient for current strategic planning. Technological advances in regulating temperature and developing resilient infrastructure also support the use of a recent reference period, as adaptation strategies have not significantly changed since 2005. Second, their reference for temperature volatility is constant over time and space, so only the level of variability matters in their calculation of the temperature anomaly variability index.

[13] To test if daily temperatures are particularly damaging when they are unusual for a given place and time of the year, Pankratz et al. (2023) combines the absolute threshold of 30°C with a location-specific threshold. The location-specific threshold is endogenously defined based on past local temperature distributions between 1980 and 1999 at firms' locations.

[14] Addoum et al. (2020) alternatively classifies daily temperature exposures relative to the historical mean number of days spent above 30°C.

[15] The construction of the temperature exposure metric in Addoum et al. (2023) is more complex than the calculation of simple statistics using temperature time series. It requires a specified function that maps marginal units of time exposure at each temperature interval to profitability among firms in a specific industry, making it more intricate than our proposed temperature metrics.

However, in our Expression (4), the reference temperature volatility $\overline{\sigma}(TA_{s,[m]})^{1960-2005}$ is not constant across states s, which affects the cross-sectional properties of TAV.

To illustrate the distinctions between TA and TAV, we consider the states of New Mexico and Arizona in the year 2017. The left panel in Figure 4 represents the TA for New Mexico (blue) and Arizona (yellow). The right panel represents TAV for the same states. Despite both states experiencing comparable average temperature anomalies in 2017, Arizona exhibits greater variability in temperature anomalies. This increased variability may reflect more frequent and severe periods of extreme heat or cold and/or greater fluctuations in temperature anomalies. This comparison underscores the possibility that states experiencing the same average temperature anomaly may nevertheless face more adverse temperature effects due to higher temperature anomaly variability. Details of the methodology for spatially aggregating each measure to the state and country levels at various frequencies, such as quarterly or yearly—which are consistent with financial data reporting periods—are provided in Appendix A.

To statistically demonstrate that TAV more accurately captures changes across the entire temperature probability distribution, we compare how TAV and TA each represent changes in the overall temperature anomaly distribution, as well as in the tails. A detailed discussion on the superiority of TAV over TA in capturing changes in the tails of the temperature anomaly distribution is provided in Appendix A.3. Here, we focus on TAV's effectiveness in describing overall changes in the entire temperature distribution. To that end, we use the Kullback–Leibler (KL) divergence—a measure of how one probability distribution diverges from a reference distribution. We first retrieve the historical temperature distribution for each month and state, setting this as our baseline. Then, we compile the distribution of realized temperatures across all combinations of month, year, and state over three distinct periods: 2005–2019, 2010–2019, and 2015–2019. By comparing these periods against the historical baseline, our objective is to describe the shifts in the temperature distribution and evaluate how well TAV and TA reflect these changes. Next, we calculate the *difference* between the historical temperature distribution and each of the three observed (realized) temperature distributions for the corresponding time frames. The *difference* is calculated using the KL divergence. This statistical distance is used to gauge the deviation at each i-th quantile of the observed distributions T from the respective i-th quantile in the historical distribution HT. [16] Analytically, we have:

$$D_{KL}(HT^{1960-2005}_{s,[m]}||T_{s,[m,y]}) = \sum_{i=1}^{D_m} HT(i)^{1960-2005}_{s,[m]} \log\left(\frac{HT(i)^{1960-2005}_{s,[m]}}{T(i)_{s,[m,y]}}\right),$$

which produces a *distance* for every location s at a monthly frequency.

To statistically determine which metric better represents the changes in temperature distribution, we regress the KL divergence on both TA and TAV. The larger the R-squared values, the better the metric captures changes in the temperature distribution. Given that KL divergence is a distance and therefore inherently positive, we use the absolute values of both TA and TAV in the regression. This approach ensures that the analysis accurately reflects the positive divergence between the pairs of distributions, thereby providing a clear comparison of their explanatory power. Table 2 reports the estimated coefficients for each regression, considering TA and TAV together and then individually, across all three time periods. The regression analysis pools observations across months, years, states, and percentile thresholds. Two observations stand out. Firstly, the R-squared values are consistently larger when TAV is included in the regression. This indicates that TAV captures more variation in the KL divergence compared to TA, demonstrating its superior explanatory power in describing changes in the temperature distribution. Secondly, the relationship between the divergence of the distributions and TAV remains consistent, even when considering more recent periods of realized temperatures. This consistency suggests that TAV continues to effectively reflect changes in temperature variability over time. In contrast, both the coefficient and R-squared of TA diminish in more recent periods. This decline indicates that TA is becoming less effective at capturing the subtleties of changes in temperature distribution over time, further underscoring the robustness of TAV as a crucial metric in this context.

[16] Since the number of days in each month, D_m, differs, the corresponding number of quantiles also varies by month.

4 The implications of temperature on returns and firm performance

In these empirical tests, we examine the effects of temperature exposure on firm returns, operational performance, and investor attention. Using the gridded temperature data, we derive state-level TA and TAV at monthly and quarterly frequencies.

We begin by studying the relationship between temperature fluctuations and the cross-section of US stock returns. By constructing a zero-cost trading strategy for each temperature metric, we compare the realized returns of firms most affected and least affected by temperature changes. This performance disparity can be attributable to changes in fundamental factors that impact firm values and business profitability, such as changes in operation performance, driven by temperature variability. Additionally, these returns may reflect changes in investor attention to temperature-related effects, where increased awareness or concern about climate risks could influence investment decisions and drive market pricing. Therefore, we investigate the operational performance of firms relative to their temperature exposure, bridging the gap between the prominent effects found in climate economics and the less definitive evidence in the financial literature. To this end, we also examine whether investors allocate more attention to climate change risks and firms during earnings calls as our metrics change.

4.1 Empirical strategy

We hypothesize that temperature impacts firm performance and assert that our statistical representations of the temperature distribution effectively capture these effects. To empirically evaluate our hypothesis, we exploit short-term temperature anomalies that provide plausibly exogenous sources of weather variation (Auffhammer et al., 2013), allowing us to identify its impact on firms. By computing the differences between historical and more recent temperature distributions at specific locations and periods—such as months, quarters, and years—we eliminate time and geographic invariant factors. This method therefore isolates the short-run random variation in weather, alongside the influence of climate change on weather outcomes, such as rising average temperatures and altered variability (Olonscheck et al., 2021).

Our primary outcome variables are at the firm level, encompassing equity returns and profitability, as well as investor attention. To determine treatment, we approximate the general location of firm operations by aligning their state-specific headquarters with our geographically aggregated temperature metrics. Due to the lack of precise operational and customer base locations—two channels likely influencing performance—we use the state count methodology developed by Garcia and Norli (2012) to exclude firms that infrequently mention their headquarters. Our assumption is that firms with more diverse geographic operations would reference multiple states aside from their headquarters. Given that temperature often acts as a blanket treatment across multiple states, as illustrated by Figure 1, this further reduces measurement bias as firms may operate across neighboring states. Additionally, we exclude firms with significant international revenue shares.[17]

Weather and firm performance may be endogenous in both the time series and cross-sectional dimensions, as firms can self-select into states based on regional weather characteristics. Our construction of temperature metrics inherently mitigates cross-sectional concerns by isolating temperature variation within states and periods. On the other hand, endogeneity over time may manifest through adaptation, with firms either relocating or investing in climate-resilient equipment. To address concerns about relocation, Appendix C.1.5 shows that most regions face similar risks in terms of temperature variability and mean changes, making relocation from vulnerable areas less feasible. Additionally, Gao et al. (2021) identifies that only 2% to 3% of Compustat firms relocate their headquarters, suggesting that such operational shifts are infrequent and, therefore, unlikely to significantly influence our estimates.

Controlling for firm investment in climate resilience poses a challenge since we cannot directly observe managerial decisions. However, results from Pankratz and Schiller (2024) suggest that adaptation efforts, such as terminating supply chain contracts, typically occur over a long-run horizon. Therefore, it is reasonable to assume that managers' decisions to adapt to climate change unfold gradually over time. To address this, our panel regressions

[17] In our robustness tests, we apply different thresholds for firm exclusion and find that higher geographic concentration or greater reliance on domestic revenues strengthens the effect of temperature variability on excess returns. Conversely, relaxing these criteria diminishes the effect, confirming that our identification strategy is functioning as intended.

include firm-by-year fixed effects, which help to minimize the influence of adaptation on our estimates.

Finally, there is evidence that temperature variability is closely intertwined with other weather phenomena, such as precipitation extremes (Allan and Soden (2008)), raising the possibility that our estimates may reflect the combined effects of both variables. To allay concerns of this omitted variable bias, we include precipitation anomalies in our robustness checks. These checks confirm that our main results persist, highlighting the independent materiality of temperature variability in our analysis.

4.2 Temperature exposure in the cross-section

We construct two zero-cost trading strategies by sorting states into five groups (quintiles) based on monthly realizations of TA and TAV experienced by 40 US states between March 2005 and December 2019.[18,19] Firm returns are then allocated to these groups based on whether their operational footprint is within those states, forming five value-weighted portfolios that are rebalanced monthly.[20] The lowest quintile portfolio contains firms experiencing lower values of TA and TAV, while the highest quintile portfolio includes firms faced with greater values of either the mean or standard deviation of the distribution of temperature anomalies, respectively. Finally, we calculate long-short (L/S) returns by subtracting the returns of firms in the lowest TA and TAV quintile from those in the highest.

Figure 5 plots the L/S returns for TAV (solid line) and TA (dashed line). The figure illustrates that a portfolio sorted by TAV generates positive abnormal returns in comparison to sorting with TA. This finding indicates that, on average, firms located in states enduring minimal changes in the standard deviation of temperature anomalies outperform those in states with greater changes.

We present this relationship numerically in the first column of Table 3, which reports

[18] As discussed in Section 2.5, we remove Alaska, Hawaii, Maine, Montana, New Mexico, Rhode Island, North Dakota, South Dakota, West Virginia, and Vermont from the sample due to the limited number of firms headquartered in these states.

[19] Later, when testing the robustness of our results, we sort states based on the absolute values of TA, so that, as with TAV, we can interpret high values of absolute TA as extreme deviations from the average temperature, encompassing both abnormally cold and abnormally hot months.

[20] For this baseline test, we remove firms that only mention their headquartered state 8.2% of the time (the 10th percentile) over all other states in their 10-K filings.

the mean excess returns net of the US risk-free rate. The first and third rows in each panel represent the monthly realized abnormal returns of the long and short strategies, respectively. The returns for the middle three portfolios are combined by averaging their respective returns, and the results are presented in the second row of each panel. The final row of Panel B, representing the returns of the L/S portfolio, shows that only the L/S strategy using TAV generates positive average monthly excess returns over the risk-free rate, at 0.39 basis points per month. The final row of Panel A indicates no significant difference in excess returns on an L/S portfolio when applying TA, suggesting firms in colder states do not perform significantly differently than those in warmer environments. This suggests that identifying whether firms operate in abnormally colder or warmer conditions is immaterial, as such information does not seem to explain returns. This finding is consistent with Addoum et al. (2020) and Addoum et al. (2023), which do not detect an immediate market response to extremely hot temperatures.

Next, we investigate the extent to which common risk factors can explain the significant average returns of the temperature-sorted L/S portfolios. The remaining columns report the alphas accounting for common risk factors, including the Fama-French three-factor model (second column), the Carhart's momentum factor and Pástor and Stambaugh's liquidity factor (third column), and the Fama-French five-factor model (fourth column). We find that the cross-sectional return spread across portfolios sorted on TAV cannot be captured by these risk factors, and the alphas in the TAV L/S portfolio remain statistically significant. The results imply that firms operating in states with lower variability in temperature consistently outperform those in more volatile temperature environments, suggesting that investors are not indifferent to temperature variability exposure.

We perform a battery of robustness checks in Appendix C to verify that the results of our L/S portfolio analysis hold and are not dependent on modeling or data choices. We begin by showing that excess returns on an L/S portfolio using the absolute value of TA (i.e., treating abnormally hot and cold temperatures similarly), remain insignificant. Next, we recognize the dependence of these results on our choices regarding geographic concentration and international revenue proportion. Adjusting these parameters, we find that excess returns increase by 5 basis points to 44 basis points when selecting firms that mention their headquartered state more than 14.1% of the time and have domestic US revenues greater than 80%. Conversely, the L/S excess returns remain significant but decrease to 30 basis points when we include firms with only 40% of their revenue originating in the US. The increase in excess returns when we tighten these criteria, and the substantial drop in excess returns when we include firms with a higher percentage of international revenue, confirms that our identification strategy is working as intended. While determining the precise operational location of a firm's activities is crucial for accurately assessing physical exposure to climate change effects, our methodology of focusing on firms with significant mentions of their headquartered state and a higher proportion of US revenue proves to be sufficiently robust.[21] We also split states into four and six groups, rather than the five quintiles used in the main analysis, to demonstrate that the observed differences persist under less or more granular sorting methods. Placebo tests that randomly assign states to different portfolios 10,000 times show that our alphas are not driven by chance, ruling out spurious correlations. Lastly, we construct a monthly transition matrix to track the movement of states between quintiles over time. This matrix reveals substantial variation, with states frequently switching from one quintile to another when sorted by either TA or TAV.

The cross-sectional tests reveal that spatial and temporal variations in firm-level TAV exposure are key for understanding the effect of temperature on firm returns. The L/S portfolio returns remain significant even when common asset pricing factors are accounted for, whereas TA proves uninformative as a metric. This underscores the importance of considering temperature variability in investment decisions; the next step is to determine the exact mechanisms driving this relationship. Conceptually, two dynamics are at play. First, temperature can impact a firm's financial performance. Changes in temperature can influence profitability through disruptions in supply or demand, which subsequently impact market prices. Second, temperature can influence investors' perceptions of firms. Increased temperature variability heightens perceived climate-related risks, influencing the demand for equities and altering the equilibrium stock price of these firms.

[21] Our methodology likely underestimates the true stock price reaction to 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.

4.3 Temperature exposure and firm profitability

The L/S portfolio results indicate that, on average, firms operating in states with minimal temperature variability consistently outperform those in more volatile temperature environments. However, some industries may be more responsive to temperature changes than others, as found in Graff Zivin and Neidell (2014), Neidell et al. (2021), and Lee and Zheng (2024). It is also plausible that particular industries benefit from volatile environments. Empirical investigations by Zachariadis and Pashourtidou (2007) and Chang et al. (2016) support this notion, identifying scenarios where atypical temperature patterns could create opportunities rather than challenges.

In this section, we investigate the operational performance of firms in relation to their temperature exposure, leveraging the exogenous geographic and time-series variation of TA and TAV. Our objective is to identify how quarterly profitability (return-on-assets)—defined as income before extraordinary items scaled by total assets—is influenced by temperature anomalies and variability. To achieve this, we sort firms into 14 industries: the 12 sectors defined by Fama and French plus construction and transportation, which are known to be sensitive to temperature variations (Graff Zivin and Neidell, 2014).

We consider the following specification:

$$\frac{Income_{i,s,t}}{Assets_{i,s,t-1}} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * TA_{s,t} + \beta_3 * D_{i,t-1} + \gamma * X + \epsilon_{i,s,t}. \tag{5}$$

where $Income$ is the income of firm i, headquartered in state s, in calendar quarter t.[22] Income is scaled by the previous quarter's total assets to produce a measure of profitability, which is then multiplied by 1,000 for interpretability. TA and TAV are the mean temperature anomaly and temperature variability, respectively, over the same fiscal quarter. The firm-level control variables, lagged by one quarter, include leverage, capital expenditure divided by sales, log book-to-market equity, earnings per share, Tobin's Q, return-on-assets, and plant, property, and equipment over assets. Generally, we use the lag of every variable other than income as they may be influenced by temperature at time t. The vector X captures firm-

[22] We exclude 171 firms that report their financial information in the first month of a calendar quarter. This adjustment ensures that our metrics, which are based on calendar quarters, better align with what firms experience in their fiscal quarters.

by-year fixed effects, isolating quarterly variations within each firm-year. These fixed effects not only account for unobservable firm-specific characteristics that remain constant over the year, but also accommodate time-varying factors such as firm adaptation strategies.[23]

We present the results in Table 4, with the first column encompassing all firms in our sample. An increase in TAV leads to significantly worse performance, indicated by lower profitability, which could subsequently result in lower returns. This finding corroborates the prior cross-sectional return analysis, confirming the negative impact of higher temperature variability on stock returns. The coefficient of -1.09, interpreted in the context of a one standard deviation increase in TAV, leads to a decline in the profitability ratio by approximately 0.48 basis points. Given the average ratio of 3.24 basis points, this represents a relative decrease of about 14.81%, underscoring the materiality of temperature variability's impact on a firm's operational performance. We observe no significant relationship between temperature anomalies and profitability, consistent with Addoum et al. (2020), who report no material effects of abnormal temperatures on establishment sales. This result highlights that variability in temperature, rather than the mean of anomalies, has a tangible impact on firm performance.

Next, we turn to industry-specific results. Columns (2) through (15) of Table 4 illustrate the effect of TAV on industry-specific profitability, revealing unique patterns. We observe a significant negative relationship between TAV and profitability for the Business Equipment, Construction, Consumer Durables, Healthcare, Manufacturing, Money (finance and insurance), and Transport industries. Additionally, non-significant negative coefficients are observed for the Non-durables, Other, Shops, and Telecom sectors. Industries such as Business Equipment, Consumer Durables, and Construction share considerable commonality, being capital-intensive and requiring substantial investments in technology and infrastructure to support production. Extreme weather and intense temperatures, as captured by increases in TAV, potentially instigate short-term capital destruction and diminish profitability. In the Transport industry, operational disruptions caused by extreme temperature events—such as ice storms and heatwaves—lead to delays, cancellations, and increased operational costs,

[23]Firms may implement adaptation strategies in response to increased temperature variability, such as investing in more resilient infrastructure or adjusting operational practices to mitigate the impact of extreme temperatures.

thereby impairing efficiency and revenue.

The Healthcare and Finance industries also tend to perform worse with higher temperature variability. For the Healthcare industry, the negative impact of high TAV values can be attributed to increased hospitalizations and healthcare costs during periods of extreme temperature. Temperature anomalies, whether extreme heat or cold, can exacerbate health conditions, leading to higher rates of hospitalization and medical interventions, especially in emergency rooms (Sun et al., 2021). Although this heightened demand for healthcare services may appear beneficial, it translates into higher costs for healthcare companies, particularly those responsible for paying hospitals and covering medical expenses. For example, emergency rooms are legally required to provide care to all patients regardless of their ability to pay, further straining healthcare providers' financial resources. Similarly, in the Finance and Insurance sector, more acute temperature variations correlate with more frequent and severe climate hazards and disasters, leading to higher payouts from insurance companies. The increased financial burden from these payouts strains insurance firms' resources, thereby reducing profitability and returns. A recent Financial Times article supports this claim, indicating that US home insurers have incurred substantial losses due to extreme weather events.[24]

In contrast, we observe a positive relationship between TAV and income for Utilities. Utilities benefit from temperature variability, with higher TAV associated with increased (unexpected) demand for electricity services, driven by the need for cooling during heatwaves and heating during cold spells.[25] However, Utilities' income is adversely affected by TA. This negative effect can be attributed to increased investments in electricity generation and transmission to meet the (expected) rise in electricity demand due to higher average temperature anomalies. In Appendix B.0.3 we demonstrate that TAV is a key determinant of unexpected electricity demand. Essentially, unexpected changes in electricity demand due to temperature variability boost the revenues of utility firms, while expected changes in demand caused by higher average temperature anomalies prompt investments in infrastructure and generation capacity.

[24]The link to the FT article 'US home insurers suffer worst loss this century', July 2024.

[25]This observation aligns with the literature documenting the sensitivity of electricity demand to temperature (Zachariadis and Pashourtidou (2007) and Chang et al. (2016)).

We also detect a positive relationship between income and TAV in the energy industry (oil, gas, and coal extraction) in Column (6). This increase is likely due to elevated demand and potential shortages of reserves and supplies because of extreme weather. Xu et al. (2023) find these effects on crude oil prices, which is plausibly impounded in the income of firms in the adjacent energy extraction industry.

This asymmetric performance can be attributed to several underlying mechanisms, identified in the extant literature and confirmed by our tests on the effects of temperature on consumption and production in Appendix B. To determine whether consumption or production channels are driving the over- or underperformance of firms in more temperature-volatile states, we analyze granular household expenditure data sourced from the US Consumer Expenditure Survey.

Starting with the impact of temperature on consumption, as reported in Appendix B.0.2, severe temperature conditions significantly affect aggregate household expenditures. Specifically, we observe reductions in spending across non-durables, durables, and apparel sectors, consistent with the coefficient directions in Table 4. This finding aligns with the "households shopping productivity" loss channel described by Starr (2000), which suggests that large temperature fluctuations create unfavorable shopping conditions, leading to reduced foot traffic and in-store sales. This observation is further supported by Roth Tran (2023) and Lee and Zheng (2024), who indicate that extreme temperatures negatively impact consumer demand and shopping behavior. Consumers tend to shift towards essential purchases or online shopping, which does not fully offset the decline in in-store sales. As a result, firms in the business equipment, retail, and durable goods sectors perform better in states with lower TAV, where consumer behavior is less disrupted. Additionally, we observe a similar pattern in the utilities sector: higher TAV is associated with increased utility expenditure, while TA shows the opposite effect.

Temperature also disrupts production by affecting labor productivity and supply chains. The frequent and intense temperature variations associated with higher TAV result in greater discomfort for workers, reduced working hours, and overall lower productivity (Graff Zivin and Neidell (2014); Neidell et al. (2021)). In Appendix B.1, we re-examine the relationship between temperature and labor productivity, finding that TAV reduces the total minutes worked on average and across various industries. These disruptions are especially pronounced in construction, where outdoor work is prevalent. As a result, construction firms in states with lower TAV—where temperatures are more stable and predictable—experience fewer disruptions and maintain higher productivity, which translates into better performance.

The results in this section strongly suggest that TAV significantly affects firms' performance across diverse industries, establishing TAV as a effective measure of temperature impacts on corporate performance. Also, the consistent impact of TAV on stock returns and operational performance across sectors underscores its materiality. This evidence validates the importance of TAV for assessing the financial implications of temperature-related risks and emphasizes its relevance for reporting and investment decisions.

4.4 Attention to temperature fluctuations

Makridis and Schloetzer (2023) document that extreme temperatures impact individuals' beliefs, linking weather conditions to psychological states, which in turn affect the formation of economic sentiment with implications for asset prices (Alekseev et al. (2021), Engle et al. (2020), Sautner et al. (2023), and Choi et al. (2020)). When temperature variability increases, the resulting uncertainty can drive individuals and organizations to seek more information and stay informed about climate change and its potential impacts. This heightened and unanticipated attention is likely related to the need to understand and mitigate the risks associated with unpredictable temperature extremes. Therefore, we suggest that temperature variability is a key driver of demand for both local- and national-level attention to climate change (Engle et al. (2020)) and analysts' attention to firm-specific climate exposure (Sautner et al. (2023)).

4.4.1 Attention at the regional and national levels

We represent local attention by gathering state-level Google search data on the topic "Climate Change". Google search activity serves as a proxy for investor attention and sentiment (Da et al. (2011); Choi et al. (2020)). Retail investors, who frequently use online resources to inform their investment decisions, may increase their search activity on climate-related topics in response to perceived risks associated with climate change. This heightened search activity can reflect growing concerns or interest in climate change, which can influence their investment behaviors. Although institutional investors may rely more on proprietary data and analysis, they are not entirely immune to broader public sentiment and media coverage. Increased search activity on climate-related topics can signal to institutional investors that climate change is becoming a more prominent concern among the general public and retail investors. This, in turn, can prompt institutional investors to consider these factors in their own investment strategies, albeit to a lesser extent than retail investors.

Investors are likely to react to unexpected temperature extremes by selling shares or demanding higher returns from firms they believe to be more exposed to adverse temperature effects. Conversely, investors might buy shares or demand lower returns from firms they perceive to benefit from temperature extremes. To test whether the metrics are related to unexpected changes in investor behaviour, we use the residuals from a lag-one autoregressive model for the state-level search indices. We then regress the AR(1) residual (innovation) of the Google search topic "Climate Change" in a particular state, s, on TAV and TA.

$$SVI_{s,t} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * TA_{s,t} + \rho_t + \gamma_s + \epsilon_{s,t}. \tag{6}$$

where ρ_t and γ_s are time and state fixed effects, respectively. All models include standard errors clustered by state to account for serial correlation of the error term within each state.

The estimated coefficients are presented in Table 5. Initially, both TA and TAV explain state-level Google search interest for the topic "Climate Change". However, when accounting for state and time fixed effects, only the relationship between TAV and state-level Google searches remains significant, as shown in panel (a) of Table 5.

Next, we use the climate change news index developed by Engle et al. (2020) to serve as our national-level climate attention index. Engle et al. (2020) constructed this index from Wall Street Journal news articles discussing climate change, aiming to capture country-wide attention on the issue. They assert that news articles on climate change are published more frequently when climate concerns are prominent. This narrative index connects increased news coverage of climate change with heightened awareness among climate risks among investors.

We regress the AR(1) residual of this climate change news index, essentially capturing the new information, on TAV and TA. To create a US-level time series for both metrics, we aggregate TA and TAV by taking the median value across all states:

$$WSJ_t = \alpha + \beta_1 * TAV_t + \beta_2 * TA_t + \rho_t + \epsilon_t. \tag{7}$$

where ρ_t is a time fixed effect.[26]

The estimated coefficients are reported in Table 6. Unexpected changes in national attention towards climate change remain positively associated with TAV than TA, after adjusting for year and quarter fixed effects. Taken together with the regional analyses, TAV, rather than TA, correlates more strongly with unexpected increases in climate-related news coverage, highlighting the impact of temperature variability on public and investor awareness.

4.4.2 Analysts' attention

The previous section suggests that temperature variability spurs retail investor attention and prompts news agencies to publish articles, heightening public and investor awareness of climate-related issues. To more directly test the influence of temperature on institutional investors, we consider the topics discussed during earnings calls. We hypothesize that greater temperature variability leads to an increase in the discussion of physical climate risks faced by the firm, as mentioned by analysts, investors, and managers in each call.

We use the physical climate exposure measure developed by Sautner et al. (2023), which uses earnings call transcripts to create a time-varying measure of firm-level exposure to physical climate change risks, hereafter $CCExposure^{Phy}$. Their methodology involves 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. Examples of selected bigrams include word combinations such as "air temperature", "global warm", and "sea level". While the universe of bigrams used in Sautner et al. (2023) does not perfectly match the risks captured by TA and TAV, there is sufficient similarity between these metrics

[26]Calculating a simple correlation between TAV and the innovations in the WSJ news index yields a Pearson coefficient of 36.12%, indicating a moderate positive relationship with the index. In contrast, the same exercise using TA results in a much weaker, negative coefficient of -11.09%.

and $CCExposure^{Phy}$ to make a meaningful comparison.

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

$$CCExposure_{i,t}^{Phy} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * TA_{s,t} + \beta_3 * WSJ_t + \beta_4 * SVI_{s,t} + \gamma_i + \epsilon_{i,s,t}. \quad (8)$$

for firm i at year t headquartered in state s. We include the innovations of the WSJ news index (WSJ_t) and the state-level Google SVI index ($SVI_{s,t}$) to distinguish the attention effects from the direct physical impacts of temperature faced by the firm.[27]

Table 7 presents the regression results for firms with that mention their headquartered state 8.2% of the time over all other states in their 10Ks and those with more than 65% of revenues from the US. 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 unanticipated climate attention at the national and state levels. This suggests that temperature variability is a contributing factor in participants' concerns regarding physical exposure to climate change, coexisting with the impact of climate-related news articles. Earnings call participants—who may or may not be located in the affected state—are aware enough to consider temperature variability occurring at the firm's headquartered state.[28] Notably, there are no significant coefficients for TA across all specifications, suggesting that average temperature anomalies alone are not substantial enough to be a topic of discussion during earnings calls.

Probing these results further, we examine whether analysts accurately incorporate temperature changes into earnings forecasts. In Appendix C, we find that TAV has a significantly negative relationship with firm-level earnings surprises. This indicates that, while analysts

[27]The results of Sautner et al. (2023), for example, show a positive relationship between the WSJ index developed by Engle et al. (2020) and their physical climate measure.

[28]Additional robustness checks in Section C reveal a stronger relationship between TAV and attention when focusing on geographically concentrated firms.

are attentive, they struggle to fully account for the impact of TAV in their forecasts. This underscores the relevance of TAV as a metric for measuring physical climate risk, even for sophisticated analysts.

5 Measuring and Reporting Temperature Risks using TAV

More than 500 institutional investors signed a 2022 statement urging governments to institute mandatory and consistent reporting of firms' *material* climate risks.[29] In parallel, regulatory bodies in the US, Europe and Australia are introducing climate-related regulatory disclosures. This pressure is exemplified by the March 6, 2024 mandate from the SEC, requiring publicly listed firms to disclose climate-related risks that could be considered material by the reasonable investor.[30] Beyond the US, the European Commission adopted the European Sustainability Reporting Standards (ESRS), which will mandate all listed companies operating within the EU to disclose the climate's impact on their operations.[31] Two requirements for firms emerge from this growing global trend in material reporting: (i) report climate-related risks that have had, or are likely to have, a significant impact on the registrant's business strategy, financial condition, or results of operations, and (ii) report the actual and potential material effects of any identified climate-related risks on the registrant's strategy, business model, and outlook.

International financial authorities and investors are increasingly demanding disclosures on both transition risks—such as direct and indirect emissions—and physical risks. While transition metrics are well-established, authorities struggle to identify practical metrics that firms can use to quantitatively report the financial effects of climate-related physical risks,

[29] This number is obtained from the 2022 Global Investor Statement to Governments on the Climate Crisis. The Statement urges alignment with the TCFD framework, which is based on material relevance.

[30] The SEC press release can be found here. Although the SEC's ruling is on hold due to ongoing legal disputes, California enacted the Climate-Related Financial Risk Act in July 2023. This legislation surpasses the domestic measures proposed by the SEC and applies to any foreign-listed companies operating in California. Consequently, approximately 10,000 firms are expected to fall under the California legislation.

[31] 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 and 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.

such as changes in temperature patterns.[32] This challenge stems from the difficulty in determining which temperature-related information is financially material for investors. Materiality can be assessed both quantitatively and qualitatively; however, the most conservative interpretations of the law require that the disclosed information be economically relevant to the extent that a reasonable investor would consider it important when making an investment decision (Katz and McIntosh, 2021). We argue that the TAV statistic satisfies the materiality criteria for disclosure as it is shown to be an effective measure of temperature's influence on firm returns, corporate performance, and investor behavior. These attributes make it an important metric for investors and regulators alike.

In this section, we outline the practical implications of our research findings and the proposed temperature variability metric, focusing on the *reporting* and *measurement* of climate-related physical risks related to temperature. These actions are essential for both corporations and investors alike, since understanding temperature risks influences strategic decisions—from selecting locations for new facilities to relocating existing operations, from making informed investment decisions to rebalancing equity portfolios. To illustrate the real-world applications of the temperature variability metric, we conduct two exercises. Section 5.1 illustrates how a firm can use TAV to report its exposure to temperature, and Section 5.2 presents a portfolio construction methodology that minimizes an investor's exposure to the future evolution of TAV.

5.1 Reporting

The first exercise involves a situation where a company, adhering to the emerging sustainability disclosure standards,[33] assesses and reports its exposure to material temperature variations in the short-term. To measure the exposure of their operations to temperature variability, a firm requires three elements: (i) a geographical footprint, (ii) the projection of TAV over the next year, and (iii) the identification of TAV risk thresholds.

[32] The 2017 TCFD Final Report notes that an area of future work is to "further develop standardized metrics for the financial sector, including better defining carbon-related assets and developing metrics that address a broader range of climate-related risks and opportunities".

[33] That is: the SEC mandate, the TCFD guidance, the EU's CSRD, the UK Climate-related Financial Disclosure (CFD), and the most recent IFRS S2 Climate-related Disclosures issued by the International Sustainability Standards Board (ISSB).

The first element is required to measure the share of a firm's activity within a geographical area of interest—one or more US states in our example—though smaller or larger regions can also be considered using the same TAV construction. In practice, the geographical relevance of each firm installation can vary depending on factors such as production output, turnover, and operating costs—information that is generally well-understood and available to firms. Alternatively, as assumed in this example, a weight can be assigned to each state proportional to the number of operating installations in that state. Once a weight has been assigned to each state, the firm's geographic operational footprint can be calculated by aggregating these weighted values, providing a weighted measure of the firm's exposure to temperature variability across its various locations.

The second element is the TAV projection. There are two main approaches: using temperature forecasts or historical simulations. For our analysis, we opt for temperature forecasts and collect open-source maximum temperature projections from the Climate Impact Lab. This organization provides scientifically supported gridded daily data aligned with the Coupled Model Intercomparison Project Phase 6 (CMIP-6).[34] By using an open-source dataset, we illustrate that reporting based on the TAV forecast can be both accessible and cost-effective. For our example, we select the temperature simulation scenario described in the Shared Socioeconomic Pathway 1, in which global warming is limited to 2.6°C above pre-industrial levels through effective carbon mitigation strategies. While climate projections provide valuable insights into regional temperature patterns, Kotz et al. (2021) argue that global climate models tend to underestimate changes in temperature variability in response to greenhouse gas emissions. This suggests that CMIP-6 models may offer conservative projections of variability changes, particularly because the model outputs are averaged across different scenarios. This averaging process can dampen the extremes, leading to lower projections of temperature variability compared to what might be observed in reality. In fact, we observe that the average projected TAV value is below zero, indicating a projected decrease in temperature variability. This value is notably lower than historical TAV values,

[34]This international initiative includes climate modeling centers worldwide, offering updated projections of future climate scenarios across various socioeconomic and emissions pathways. We specifically use the CMCC-ESM2 climate model, which has demonstrated proficiency in projecting temperature trends over broad geographical areas (Firpo et al., 2022). Data are collected using Microsoft's planetary computer available here.

suggesting that future temperature variability may be underestimated. To address this, we adjust the TAV values by recentering them around zero. Alternatively, TAV projections can be based on historical data, such that future TAV values are projected based on past realizations of TAV. This historical method has the advantage of being straightforward and based on actual recorded data, making it a practical choice for firms without access to climate modeling simulation data. By using historical data, companies can create a baseline of expected temperature variability based on their own operational history. Also, this approach can be particularly useful for regions where long-term climate forecasts are uncertain or unavailable.[35]

The third component involves identifying TAV thresholds to categorize temperature variability risk as: high, medium, and low TAV risk. The threshold identification process is flexible and can easily be tailored to meet specific supervisory requirements, including the addition of more thresholds as needed. We begin by retrieving historical TAV data and ranking states based on their TAV values from lowest to highest. Following the method used in constructing the long-short portfolio, we divide the ordered list into quintiles, creating five distinct groups of states with varying levels of temperature variability. We then define the upper threshold (TH1) in line with the state in the first quintile with the lowest TAV.[36] Similarly, the state in the third quintile with the lowest TAV defines the lower threshold (TH2). Next, we gather temperature simulation data for each state. States with projected TAV values above TH1 are classified as having high exposure, while those with values below TH2 are classified as having low exposure. States falling between these thresholds are categorized as having medium exposure.

The steps described here are applied to two active companies: American Electric Power Company Inc (AEP) and APU Resource Group. We obtain the number of installations in each US state for each company from S&P. Regarding the construction of their geographical footprint, we assume each installation contributes equally to the companies' operations, and thus weight them equally. Columns (3) and (5) in Table 8 report the percentage of

[35] It is important to note that while historical data provides a tangible and empirical basis for TAV projections, it may not fully capture future change in temperature patterns. Climate change may introduce new variability trends not predicted by historical data alone.

[36] This is equivalent to selecting the state in the second quintile with the highest TAV.

installations by state for AEP and APU, respectively. Columns (4) and (6) show the firms' aggregate percentages of exposure across the three risk categories. For example, AEP (Firm 1) has 25.9% of its production in Oregon, which is forecasted to be above TH1 (high exposure).

This exercise illustrates how the geographic and projected TAV variations provide a simple framework for comparing relative temperature exposures across firms. Moreover, this approach can be adapted to consider different time horizons, enabling firms to evaluate both short- and long-term climate-related risks based on their unique operational footprints.

5.2 Taking the temperature of a portfolio

In the second exercise, we focus on portfolio managers who increasingly seek to diversify their investments to manage climate-related physical risks. Specifically, we demonstrate how TAV can be incorporated into portfolio optimization as a constraint within mean-variance allocation models, to account for temperature risk.

When considering additional allocation constraints related to temperature risk, portfolio managers have several options. One straightforward approach is to implement a screening process. This involves ordering all firms within the investment universe based on their TAV exposure, and systematically excluding those firms that exceed a subjectively identified TAV threshold. This method effectively filters out companies most exposed to temperature variability, allowing the portfolio manager to focus on investments with lower associated climate risks. Alternatively, portfolio managers can rebalance their portfolio using standard mean-variance optimization, while also incorporating a TAV constraint. This approach allows the portfolio to maintain its desired risk–return profile while controlling for temperature variability exposure.

To illustrate a rebalancing strategy, we present a simple example focusing on firms headquartered in the top 10 US states by the number of firms. This gives us a hypothetical equity investment universe consisting of 1,159 firms in our sample. Starting with random initial portfolio weights for the baseline portfolio, we compute the portfolio's mean return, variance, and TAV as follows $TAV_p = \sum_{i=1}^{n} \omega_i TAV_i$, where ω_i represents the weight of each stock in the portfolio and TAV_i represents the temperature variability exposure of each firm. Table 9 provides the percentage concentration of the portfolio in each state before any rebalancing for TAV. Next, we apply TAV as a constraint, aiming to keep the portfolio's overall TAV below a pre-defined threshold. To set this threshold, we follow the method described in Section 5.1, selecting the TAV of the state at the lower bound of the third quintile as the ceiling. With this threshold established, the portfolio is rebalanced to maintain a comparable risk–return profile while ensuring that the portfolio's TAV remains under the ceiling. Rebalancing for TAV does not merely exclude states with high-temperature variability. Instead, as shown in Table 9, the strategy entails adjusting geographic allocations to manage the trade-off between temperature exposure and portfolio returns and variance. For example, while the allocation to Florida—having the highest TAV—was reduced from 21% to 5%, the allocation to the second most exposed state Ohio was increased from 2% to 12%. This demonstrates that rebalancing seeks to optimize returns and minimize temperature variability without entirely discarding high TAV states.

This exercise demonstrates how portfolio managers can integrate temperature risk management into their strategic asset allocation decisions using TAV. With TAV being easily replicable across regions, the approach is scalable and standardized, making it adaptable for broader investment strategies.

6 Conclusion

Stuart Kirk, former head of responsible investing at HSBC Asset Management, voiced frustration at the burdensome regulations his team faced regarding the disclosure of financial risks from climate change.[37] Aside from the sheer volume of paperwork, disclosures are unstandardized and may not be based on financial materiality.[38] This means investors must wade through an overwhelming amount of information necessarily without deriving any benefit from it (Ilhan et al. (2023)). We believe that developing a scalable, standardized, and materially relevant metric for one of climate change's most consequential effects—changing

[37]See the video, "HSBC's Stuart Kirk tells FT, investors need not worry about climate risk".

[38]Financial materiality is a legal term as defined by the U.S. Supreme Court: "a matter is material if there is a substantial likelihood that a reasonable investor would consider it important when determining whether to buy or sell securities".

temperature distributions—is an effective way to address some of these challenges.

Our paper offers a robust way of quantifying this material risk to firm performance. Tracking changes in the variability of temperature anomalies across geographic and temporal dimensions allows for quantitative, standardized, and comparable disclosures of material climate risks, which are causally linked to financial, behavioral, and economic outcomes.

A portfolio that shorts firms operating in states with high temperature variability, and goes long on those in less volatile states, generates 39 to 43 basis points in excess returns per month. Quarterly firm income significantly declines with greater temperature variability, indicating that the observed return reaction reflects fundamental changes in firm value. Part of this return response can be attributed to an attention channel—the media responds to high-temperature variability by publishing more climate articles, and investors adjust their beliefs in response to temperature variability. Additionally, increased temperature variability leads to declines in both expenditure and minutes worked, highlighting both consumption and production-side effects.

Our metric provides a practical way to evaluate firms' exposure to climate-related physical risks, such as shifts in temperature distribution, using standardized, publicly available data from independent sources. The methodology is adaptable, allowing it to be scaled across various geographies and applied over different time horizons. These features make it a straightforward solution for firms, investors, and government agencies in addressing the climate risk information gap.

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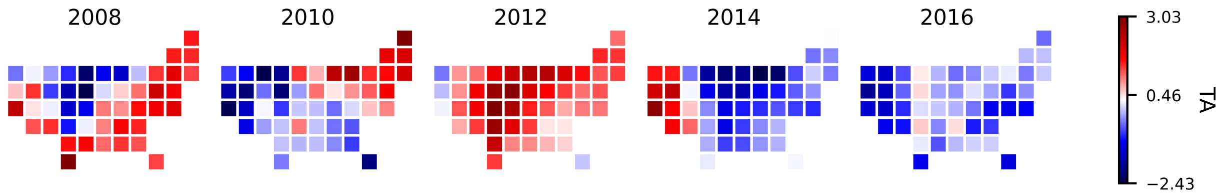
7 Figures

Figure 1: Geographic and time-series variation of temperature statistics

(a) Yearly Mean Temperature Anomalies



(b) Yearly Standard Deviation of Temperature Anomalies

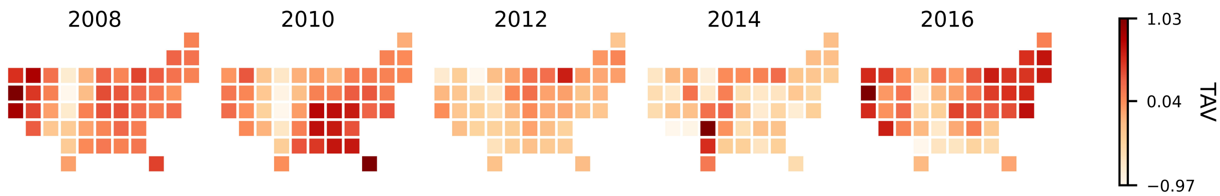
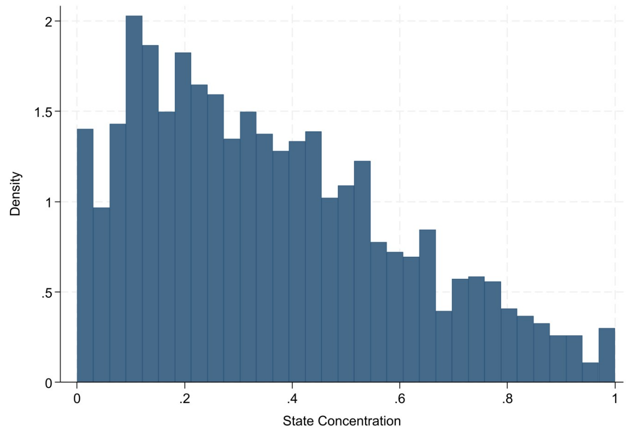


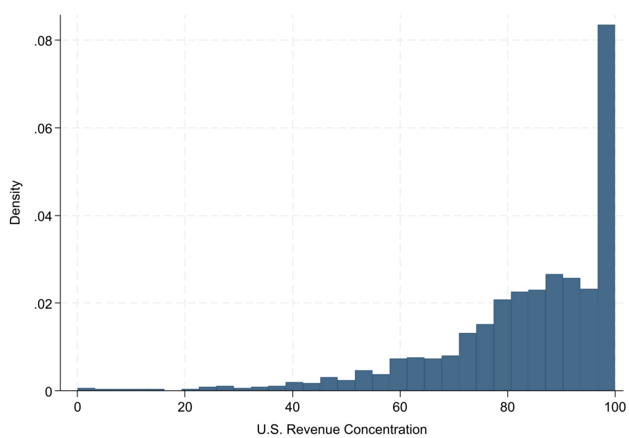
Figure 1 shows the yearly mean of temperature anomalies (TA) or variability of temperature anomalies (TAV) for states in the contiguous US in graphs A and B, respectively. The base period for calculating the metrics is 1960-2005. For graph A, blue regions are colder than the base period while red regions are hotter. For graph B, light red regions have lower variability than the base period while darker red represents higher variability.

Figure 2: Geographic concentration of firms in the Russell 3000 based on 10-Ks



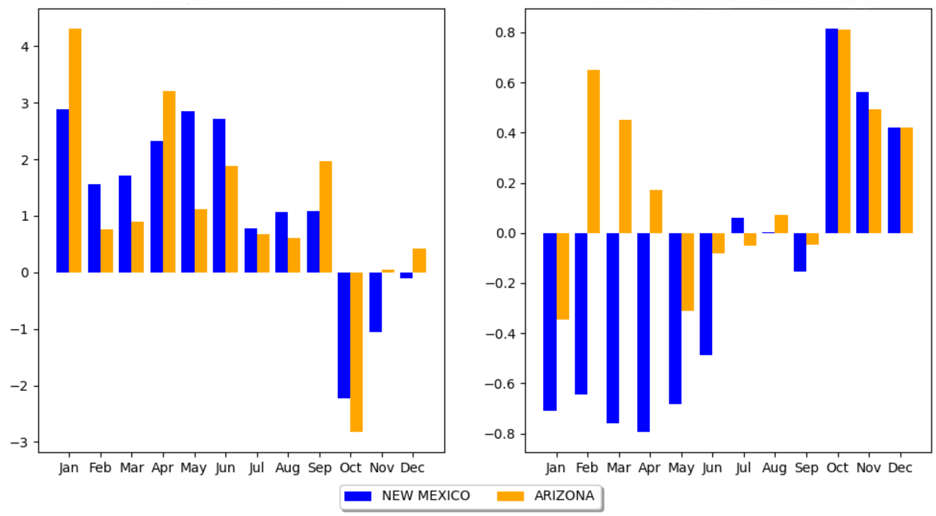
This histogram represents the geographic concentration of firms in our sample using the methodology outlined in Garcia and Norli (2012) and Bernile et al. (2015). We use a 10-K-based measure of firm local exposure. We parse the 10-K filings of all Russell-3000 firms for each year to identify the number of times the US states and Washington DC are mentioned in sections 1A, 2, 6, and 7 of the Form 10-Ks. The firm-headquarter citation count is calculated by dividing the total number of mentions of the headquartered state by the total mentions of all US states and Washington DC. Then, we average this for each firm to obtain a metric that we define as the 10-K measure of state operational dispersion. If the average number of mentions is closer to one, it indicates that the firm predominantly mentions their headquartered state. Conversely, if the average is lower, it signifies a broader distribution of operations.

Figure 3: US revenue concentration of firms in the Russell 3000 based on 10-Ks



This histogram shows a left-skewed distribution of US revenue concentration, indicating a range of domestic and international sales exposure among firms. We set a 65% threshold, corresponding approximately to the 10th percentile, to exclude firms with significant sales outside the US.

Figure 4: TA and TAV in New Mexico and Arizona



The left panel represents the Temperature Anomaly (TA) for New Mexico (in blue) and Arizona (in yellow). The right panel shows the Temperature Anomaly Variability (TAV) for the same states. The year of reference is 2017. Bars above (below) the zero line indicate temperature anomalies and variability, respectively, above (below) the historical average. Despite both states experiencing comparable average temperature anomalies in 2017, Arizona exhibits greater variability in temperature anomalies.

Figure 5: Unadjusted long-short returns of portfolios sorted on TA and TAV

Figure 5 presents the long-short portfolio returns sorted either on US state exposure to temperature anomalies (TA) or variability of temperature anomalies (TAV). The long-short portfolio methodology consists of sorting 40 states into exposure quintiles 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 least vulnerable portfolio based on either TA or TAV.

8 Tables

Table 1: Descriptive statistics

	Mean	SD	P10	P25	P50	P75	P90	N
Temp Anomaly (TA)	0.48	(1.20)	-0.89	-0.19	0.44	1.11	1.90	99,335
Temp Anomaly Variability (TAV)	0.13	(0.44)	-0.41	-0.15	0.09	0.42	0.70	99,335
Near State, %	35.70	(23.26)	8.19	16.84	31.91	50.84	69.69	99,335
Domestic Income Earned, %	83.91	(16.94)	60.77	76.35	88.03	98.24	100.00	71,304
Leverage	0.24	(0.21)	0.00	0.05	0.20	0.37	0.53	98,839
Invest Rate	0.16	(0.39)	0.00	0.02	0.06	0.14	0.35	97,049
Book to Market Equity, Ln	-0.86	(0.78)	-1.91	-1.30	-0.76	-0.30	0.02	94,844
Earnings Per Share	0.45	(0.85)	-0.22	0.05	0.34	0.71	1.27	98,289
Tobin's Q	2.07	(1.50)	1.00	1.13	1.53	2.35	3.82	97,973
Profitability	3.24	(42.52)	-21.68	1.62	8.59	19.96	34.04	96,033
ROA	2.57	(42.59)	-22.53	1.53	8.36	19.45	33.06	98,339
PPE/Assets	0.20	(0.21)	0.01	0.03	0.12	0.29	0.56	91,994
Firms								2,240

This table presents summary statistics of the generated variables and firm fundamentals from Compustat. Temperature anomaly, TA, represents the difference between the mean temperature anomaly for each quarter from 2005 to 2019 and the mean temperature anomaly from 1960 to 2004 for 40 US states. Temperature anomaly variability, TAV, is calculated similarly, but uses the standard deviation of temperature anomalies within a quarter. The underlying temperature data is obtained from Berkeley Earth Surface Temperatures gridded data, with each grid cell representing a 1-degree latitude by 1-degree longitude area. 10 US states are excluded as they have minimal firms headquartered there: Alaska, Hawaii, Maine, Montana, New Mexico, Wyoming , North Dakota, Vermont, South Dakota, and West Virginia. Near state represents the percentage of time a firm mentions their headquartered state over all other US states mentioned in their 10Ks from 2005-2019 multiplied by 100. Domestic income earned is the percentage of revenue earned domestically, calculated from Compustat segment data. Leverage is calculated quarterly debt over total assets (dlttq+dlcq/atq). Investment rate is yearly capital expenditure over quarterly sales (capxy/saleq). Book to market rate is calculated using shareholders equity over market equity ((seqq + txditcq - pstkq)/(prccq*cshoq)) and transformed to a log form. Earnings per shape is net income including extraordinary items over shares outstanding (niq/cshoq). Tobins Q is calculated as follows (atq +(cshoq*prccq) - ceqq)/atq. Return on assets is calculated using net income over assets (ibq/atq). Profitability is similar to ROA except that atq is lagged by one quarter. PPE/Assets is property, plant, and equipment over total assets (ppentq/atq). The sample period is from 2005 - 2019 at a quarterly frequency.

Table 2: Kullback-Leibler divergence of the temperature anomaly distribution

	2005-2019 (a)			2010-2019 (b)			2015-2019 (c)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
|TA|	0.384		1.782	0.327		1.6304	0.211		1.588
	(8.855)		(36.075)	(6.135)		(38.359)	(2.395)		(26.224)
|TAV|	5.754	6.397		5.700	6.251		5.970	6.312	
	(32.015)	(41.702)		(26.214)	(39.882)		(17.867)	(26.516)	
R Sq	0.568	0.552	0.295	0.574	0.567	0.284	0.569	0.566	0.251
Obs	8640	8640	8648	5184	5184	5184	2304	2304	2304

This table presents results showing that changes in the standard deviation, TAV, more effectively represents the distribution of temperature anomalies across time than the changes in the mean, TA. Specifically, we regress the Kullback–Leibler (KL) divergence on the absolute value of TA and TAV across three periods. The KL divergence measures the deviation of historical monthly state temperatures from a baseline distribution. We calculate differences between historical temperatures and observed distributions for three periods: 2005-2019, 2010-2019, and 2015-2019 to reflect changes in temperature distributions. The baseline is from 1960 to 2004. These panel regressions quantitatively assesses how well TAV and TA capture these shifts. T-statistics are reported in parenthesis.

Table 3: Abnormal returns to portfolios sorted on temperature metrics

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.779**	0.079	0.086	0.099
	(0.025)	(0.444)	(0.420)	(0.316)
Portfolios 2,3,4	0.691**	0.037	0.013	0.020
	(0.029)	(0.488)	(0.833)	(0.669)
Portfolio 5	0.893***	0.240*	0.198	0.206
	(0.003)	(0.062)	(0.108)	(0.127)
Portfolio 1 - 5	-0.114	-0.161	-0.112	-0.107
	(0.528)	(0.362)	(0.529)	(0.557)

Panel B: Portfolios sorted on TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.055***	0.374***	0.404***	0.335***
	(0.001)	(0.001)	(0.002)	(0.003)
Portfolios 2,3,4	0.666**	0.018	-0.035	-0.007
	(0.031)	(0.776)	(0.554)	(0.907)
Portfolio 5	0.683*	-0.064	-0.047	-0.055
	(0.065)	(0.456)	(0.596)	(0.513)
Portfolio 1 - 5	0.372**	0.437***	0.451***	0.391**
	(0.014)	(0.004)	(0.005)	(0.011)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). Each month t, we sort U.S. states into five groups (quintiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 5 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle three portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors. "Portfolio 1–5" reports the return spread between portfolios 1 and 5, i.e., the return difference between the least and most exposed portfolios. To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated in the U.S. The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 4: Temperature exposure and firm profitability

	(1) All	(2) BusEq	(3) Chems	(4) Cnstr	(5) Durbl	(6) Enrgy	(7) Hlth	(8) Manuf	(9) Money	(10) NoDur	(11) Other	(12) Shops	(13) Telcm	(14) Trans	(15) Utils
TAV	-1.09***	-2.13***	-1.30	-2.38**	-2.26*	1.95**	-2.16**	-0.89*	-0.39*	-0.89	-1.53	-0.78	-0.12	-1.32**	0.66*
	(-3.37)	(-3.91)	(-1.14)	(-2.71)	(-1.96)	(2.37)	(-2.68)	(-1.99)	(-1.75)	(-1.07)	(-1.48)	(-1.37)	(-0.09)	(-2.09)	(1.76)
TA	0.04	-0.07	-0.02	0.26	0.36	-0.33	0.35	0.03	0.03	0.29	-0.25	-0.14	0.36	0.40**	-0.55***
	(0.34)	(-0.49)	(-0.08)	(1.02)	(1.42)	(-0.84)	(0.59)	(0.15)	(0.44)	(1.24)	(-0.78)	(-0.55)	(0.88)	(2.26)	(-3.32)
L.Leverage	-5.34	-6.79	27.43	9.21	-27.92	31.28	-18.34	13.12	-4.55	-5.02	-28.06***	15.11	-45.24**	1.60	90.09***
	(-1.01)	(-0.87)	(0.53)	(0.62)	(-0.88)	(0.75)	(-1.32)	(0.71)	(-0.79)	(-0.31)	(-3.27)	(0.77)	(-2.89)	(0.09)	(6.87)
L.Invest Rt	-1.03	-6.43**	-6.49***	-4.75	9.82*	0.68	-0.79	-3.82	-1.75	-5.56	-1.02	-2.81	0.18	0.32	-0.70
	(-1.21)	(-2.29)	(-3.23)	(-0.81)	(1.89)	(0.56)	(-0.30)	(-1.39)	(-1.43)	(-0.66)	(-0.62)	(-1.19)	(0.24)	(0.34)	(-1.23)
L.Bk to Mkt	-12.67***	-19.17***	-17.95***	-16.78***	-8.84*	-20.50***	-9.01**	-22.45***	-3.85**	-3.95	-17.32***	-9.72***	-17.49***	-10.67**	-0.66
	(-10.54)	(-3.83)	(-3.68)	(-4.27)	(-1.81)	(-4.10)	(-2.47)	(-6.12)	(-2.21)	(-0.68)	(-2.81)	(-3.83)	(-3.36)	(-2.70)	(-0.50)
L.Earn/Shr	-2.09***	0.53	-1.46	3.22*	3.79*	-2.72***	-8.81***	0.05	-0.16	-2.74	-0.38	-1.37	-2.03	-0.87	-0.99
	(-4.57)	(0.30)	(-0.74)	(1.99)	(1.83)	(-4.47)	(-5.95)	(0.05)	(-0.44)	(-1.46)	(-0.29)	(-1.66)	(-0.90)	(-0.79)	(-1.67)
L.Tobins Q	-3.84***	-4.27**	-4.76*	-0.18	-0.61	0.14	-5.05***	-4.68**	2.90	0.85	-4.45*	1.94	-6.56*	-4.68*	15.10***
	(-9.08)	(-2.58)	(-1.89)	(-0.11)	(-0.22)	(0.03)	(-9.07)	(-2.47)	(1.12)	(0.55)	(-1.94)	(1.60)	(-1.80)	(-1.89)	(2.93)
L.ROA	8.93	-74.38	8.86	-210.87**	-177.38	150.51*	110.76***	-24.33	-90.99**	-81.06*	-89.48	-59.84	-102.41	-25.44	-141.19***
	(0.40)	(-1.29)	(0.08)	(-2.62)	(-1.30)	(2.17)	(5.28)	(-0.76)	(-2.35)	(-1.88)	(-1.23)	(-1.06)	(-0.91)	(-0.31)	(-3.83)
L.PPE/Asset	-16.89	-38.20	-26.57	-14.53	-71.67	25.96	-65.79	27.99	2.82	14.38	37.90*	-34.46	25.37	-23.11	-50.54***
	(-1.15)	(-1.48)	(-0.49)	(-0.37)	(-1.02)	(1.03)	(-0.90)	(1.02)	(0.11)	(0.88)	(1.84)	(-1.60)	(1.46)	(-1.26)	(-4.60)
Constant	8.50**	1.97	1.43	0.91	25.87	-20.62	-8.87	-5.24	1.99	12.53*	2.18	8.22	13.63	27.31***	-6.65
	(2.43)	(0.40)	(0.10)	(0.08)	(1.33)	(-1.62)	(-1.00)	(-0.63)	(0.86)	(1.71)	(0.60)	(1.27)	(1.58)	(3.22)	(-0.81)
IndYr FE	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No
FirmYr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Sq	0.73	0.68	0.75	0.46	0.73	0.41	0.80	0.56	0.64	0.49	0.52	0.52	0.46	0.64	0.24
Obs	60951	8071	1385	2729	1411	1335	6506	6103	14357	3669	4011	4354	1274	2593	3153

This table presents the results of regressing quarterly income, scaled by total assets from the prior quarter, to the quarterly mean of temperature anomalies (TA) and the standard deviation of temperature anomalies (TAV). The control variables include leverage, capital investment rate, log book-to-market equity, Tobin's Q, return on assets, earnings per share, capital expenditure, and plant, property, and equipment over total assets, all from the previous quarter. To control for operational dispersion, we select firms that mention their headquartered state 8.2% of the time (10th percentile) over all other states in their 10K filings and firms with more than 65% of revenues in the US. The quarterly sample period is from 2005 to 2019. All specifications include firm by year fixed effects. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

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

	(1)	(2)	(3)	(4)
TAV	3.692***	3.929***	0.919**	0.999**
	(6.17)	(6.35)	(2.36)	(2.40)
TA	-0.511***	-0.489***	-0.106	-0.097
	(-4.16)	(-3.89)	(-0.84)	(-0.74)
State FE	No	Yes	No	Yes
YearxQuarter FE	No	No	Yes	Yes
Adj R Squared	0.020	0.004	0.716	0.711
Observations	2950	2950	2950	2950

This table presents results associating the innovations in the Google Search topic "Climate Change" to the mean of temperature anomalies (TA) and the standard deviation of temperature anomalies (TAV) at the state-level. 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 are reported 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	1.638**	1.935***	1.519**
	(2.064)	(3.250)	(2.159)
TA	-0.069	-0.089	0.098
	(-0.365)	(-0.558)	(0.622)
Fixed Effect	None	Quarter	Yr Quarter
Adj R Squared	0.098	0.339	0.489
Observations	50	50	50

This table presents results associating the innovations in the national Wall Street Journal news index developed by Engle et al. (2020) to the mean of temperature anomalies (TA) and the standard deviation of temperature anomalies (TAV). The attention index at the quarterly frequency and multiplied by 1,000, is regressed onto TA and TAV with varying fixed effects. T-statistics are reported 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

	(1)	(2)	(3)	(4)
TAV	4.147**	5.095**	3.529**	4.488**
	(2.648)	(2.656)	(2.245)	(2.442)
TA	-0.733	0.245	-0.689	-0.045
	(-0.724)	(0.314)	(-0.659)	(-0.050)
WSJ Innov		1.517*		0.416
		(1.821)		(0.333)
SVI Innov			0.144**	0.124
			(2.342)	(1.480)
Firm FE	Yes	Yes	Yes	Yes
R Squared	0.075	0.063	0.081	0.068
Obs	15864	13136	15103	12375

This table presents results associating the physical climate exposure attention index developed by Sautner et al. (2023) to the mean of temperature anomalies (TA) and the standard deviation of temperature anomalies (TAV). The yearly innovations in the attention index is regressed onto TA and TAV with varying fixed effects. We control for national and state-specific attention towards climate change. *WSJ Innov* represents the innovations in the national Wall Street Journal news index developed by Engle et al. (2020). *SVI Innov* represents innovations in the Google Search topic "Climate Change" at the state level. We select firms that mention their headquartered state 8.2% of the time over all other states in their 10Ks and those with more than 65% of revenues from the US. The sample period is from 2005 to 2019. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 8: Reporting exposure to changes in temperature variability

TAV Exposure	State (1)	TAV (2)	Firm 1 Installations (3)	Firm 1 Exposure (4)	Firm 2 Installations (5)	Firm 2 Exposure (6)
High	CA	1.37	0.7%	26.7%	0.0%	11.9%
	OH	1.07	0.0%		11.9%	
	OR	1.03	25.9%		0.0%	
Medium	TX	0.40	3.0%	37.0%	30.4%	30.4%
	MN	0.09	20.7%		0.0%	
	ND	-0.25	8.9%		0.0%	
	WY	-0.34	4.4%		0.0%	
	SD	-0.43	10.4%		0.0%	
	WW	-0.52	0.0%		34.1%	
Low	ID	-0.59	8.9%	36.3%	0.0%	57.8%
	IA	-0.63	0.7%		0.0%	
	OK	-0.65	0.0%		6.7%	
	MT	-0.73	16.3%		0.0%	
	AR	-1.00	0.0%		17.0%	

This table demonstrates the exposure of installations for American Electric Power Company (Firm 1) and APU Resource Group (Firm 2) to TAV projections for 2025. The left most column categorizes US states into high, medium, or low exposure based on TAV terciles. TAV derives from gridded daily data following CMIP6 and the CMCC-ESM2 climate model. Columns (3) and (5) present the percentage of installations by state for the two firms, using S&P data. Columns (4) and (6) show the firms' total production percentages across the three risk categories.

Table 9: Optimizing portfolio temperature exposition

		Portfolio Weights	
Stato	State TAV	Initial	Optimized
CALIFORNIA	-0.85	2.3%	13.4%
NEW YORK	0.37	0.9%	4.9%
TEXAS	0.29	20.4%	17.3%
MASSACHUSETTS	-0.92	13.6%	11.9%
ILLINOIS	0.29	6.4%	11.2%
PENNSYLVANIA	-1.26	3.7%	3.4%
FLORIDA	1.31	21.8%	4.8%
OHIO	0.73	2.0%	11.6%
NEW JERSEY	0.71	19.5%	13.3%
GEORGIA	-0.45	9.5%	8.2%
Portfolio TAV		0.29	0.04

This table presents the optimization results for a portfolio consisting of firms headquartered in the top 10 states by the number of companies, collectively representing almost 40% of Russell 3000 constituents. The second column shows the TAV forecast for each state. The third column displays the portfolio's initial weights, alongside the portfolio's overall TAV, calculated as the weighted average of state-level TAV. The final column reports the portfolio weights after rebalancing, with TAV incorporated as a constraint. The objective of this rebalancing is to keep the total TAV exposure below the threshold set by the TAV of the state at the lower bound of the third quintile..

A Appendix A

A.1 Spatial Aggregation

We explain the process of spatially aggregating the temperature data and illustrate our measures of temperature anomaly (TA) and temperature anomaly variability (TAV), first aggregated at the US state level and then at the country level.

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

$$T_{s,[d,m,y]} = \sum_{i=1}^{N_s} w_i \cdot T_{i,[d,m,y]}, \tag{9}$$

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, and w_i is the weight associated with the grid cell. In this specific case, we assign equal weight to the grid cells by setting the weights w_i equal to $1/N_s$.[39] Thus, $T_{s,[d,m,y]}$ is an equally weighted average of the temperature assigned to each grid cell in state s. Alternative methods for aggregation, such as by population, wherein the weight represents the proportion of the population within a grid cell, are discussed in Appendix A.2. This spatial aggregation enables us to derive TA and TAV for each state s in the US, as outlined in expressions (1) and (4).

Figure 1 highlights the state-level measures of TA and TAV across the US for the selected years 2008, 2010, 2012, 2014, and 2016.[40] Panel (a) illustrates the yearly TA values for each state, with blue indicating colder-than-normal regions, and red indicating warmer-than-normal regions. Panel (b) outlines TAV, where darker shades represent greater variability compared to historical records, and lighter shades represent lower variability. The figure distinctly contrasts the two metrics, illustrating both the temporal variation and spatial heterogeneity between them.

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

[40] In Section 3 we use the monthly realization of each temperature metric; however, this can easily be extended to a yearly frequency.

A.2 Alternative construction of temperature variables

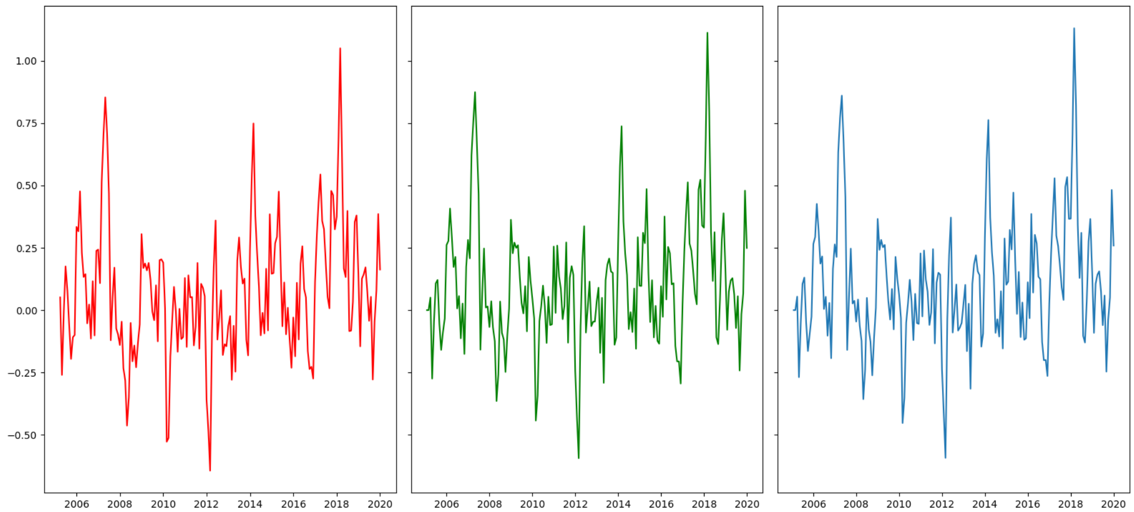
In the previous section, we detail the construction of $T_{s,[d,m,y]}$, which represents an equally weighted average of the temperature attributed to each grid cell within state s. While this equal weighting simplifies aggregation, it may overlook specific state characteristics. This issue becomes evident when evaluating the US-wide temperature metrics, where each state is treated as a single cell. The challenge in national aggregation lies in selecting the proper weight for each state. Using an equal weight suggests that a significant TAV in a smaller state would influence the final index as much as the same TAV in a larger state. Hence, the weighting mechanism must reflect the relative importance of each state within the national context.

Two natural choices for weighting emerge: GDP-based weights and population-based weights. Since neither GDP nor population data is available at monthly frequencies (GDP is quarterly and population data is yearly), we forward-fill the data to derive a monthly series compatible with TA and TAV. Using GDP-based weights emphasizes economically productive regions, translating the temperature anomalies' economic impact into the final analysis. Conversely, population-based weights prioritize human experiences; thus, greater variability in a densely populated state holds more significance than in a sparsely populated one. Figure 6 contrasts the US-wide TAV index based on three different weighting criteria. A quick visual comparison of the three measures reveals minor differences, particularly when contrasting equal weighting with population or GDP-based weights.

A.3 Temperature Extremes

While prior research statistically demonstrates that changes in variability, rather than changes in mean, better represent extremes in the temperature distribution (Katz and Brown (1992)), in this section we show explicitly how TAV generally outperforms TA in detailing dynamics at the extremes of temperature distributions. By comparing how well TA and TAV capture the spectrum of extreme temperature days—ranging from moderately to intensely cold or hot—we find that TAV is effective in representing a broad range of temperature realizations used in other literature.

Figure 6: TAV construction using three different weighting criteria



This figure presents TAV construction using three different weighting criteria. The first uses an equal-weighted index construction, where $W_i = 1/N_i$ with $N_i = 50$. The second uses a population-based weighting method, defined as $w_i = pop_{i,t}/\sum_i pop_{i,t}$. The third uses state GDP as the weight, defined as $w_i = GDP_{i,t}/\sum_i GDP_{i,t}$

To quantify the number of unusually cold and hot days by specific dates (day d, month m, year y) and locations, we examine the temperature anomaly distribution from 2005 to 2019 for each state s, following the steps described in Section 3. Using matching percentile pairs from the historical temperature anomaly distribution (1960–2004), we define extreme temperature days using cutoff points from the 5th to the 30th percentile for cold days, and from the 70th to the 95th percentile for hot days. These state-specific percentiles align with corresponding calendar days and months, reflecting different frequencies and intensities of temperature extremes. We then determine the *number of days* in a month that exceed these thresholds.

This methodology consolidates various approaches in the emerging financial literature that link financial outcomes to temperature extremes. For example, Pankratz et al. (2023) and Addoum et al. (2020) categorize extremes using a 30°C threshold, associating worker performance declines beyond this point. Addoum et al. (2023) extends this by examining the effects of the entire temperature distribution on firms' earnings news—notably including colder extremes. To address adaptation concerns, Acharya et al. (2022) and Pankratz et al. (2023) compare realized temperatures against historical distributions. Consequently, the percentile approach used in this paper, combined with differentiating realized temperatures from historical values, integrates these methodologies while accounting for regional adaptation.

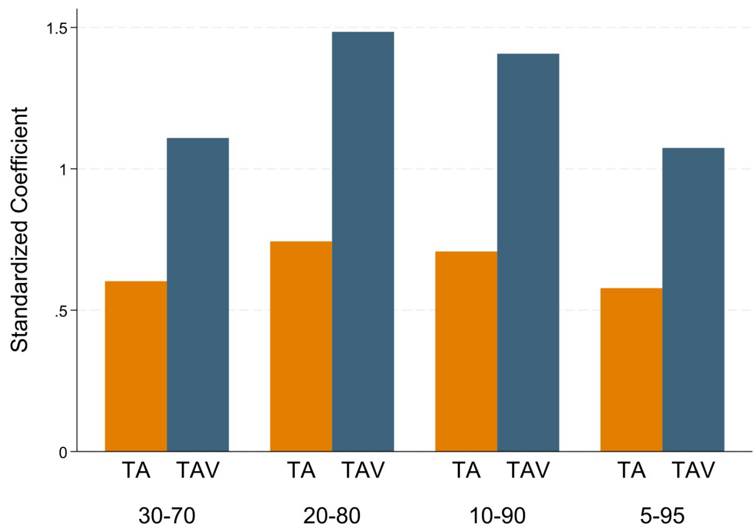
We compute the number of days in a month that exceeds particular percentile pairs, which represent extremes in either tail of the temperature anomaly distribution. This count serves as the dependent variable in pooled regressions to examine the magnitude of the relationship between the dependent variable and the regressors, TA and TAV. Figure 7 shows the standardized coefficients of TA (orange) and TAV (blue)—coefficients multiplied by the metrics' respective standard deviations—across four percentile pairs (30th and 70th, 20th and 80th, 10th and 90th, 5th and 95th). The substantially greater coefficients for TAV across all sets of percentiles indicate its effectiveness in capturing the incidence of extreme temperature days, both cold and hot. Generally, a one-standard-deviation increase in TAV corresponds to more than one additional day of temperature extremes in a month. In contrast, TA displays a notably weaker relationship with the frequency of extreme temperature days.

Next, we focus on the right tail of the temperature anomaly distribution which is relevant as most extant literature only studies heat extremes. Instead of counting the number (*frequency*) of extreme days, we explore how TAV and TA relate to the *intensity* or *severity* of extreme temperatures on days surpassing a defined threshold. Investigating severity is important because the magnitude of these exceedances is relevant for the magnitude of damages.[41] As climate change continues to intensify extreme temperatures and consistently break temperature records each year, it is warranted to represent the severity of heat due to its profound effects on human behavior and economic outcomes. To calculate intensity, we use historical (1960–2004) percentile thresholds—specifically the 70th, 80th, 90th, and 95th percentiles—of the temperature anomaly distribution for each state and month. These thresholds are then applied to the recent period (2005–2019) to compute the mean temperature of the days exceeding these thresholds within a given month, thus capturing the severity of extreme temperatures.

To study the relationship between temperature metrics and the intensity of temperature anomalies, we regress the state-level monthly mean temperature anomaly, conditional

[41] Somanathan et al. (2021) find greater reductions in worker productivity if temperatures breach 35° C compared to a threshold of 30° C.

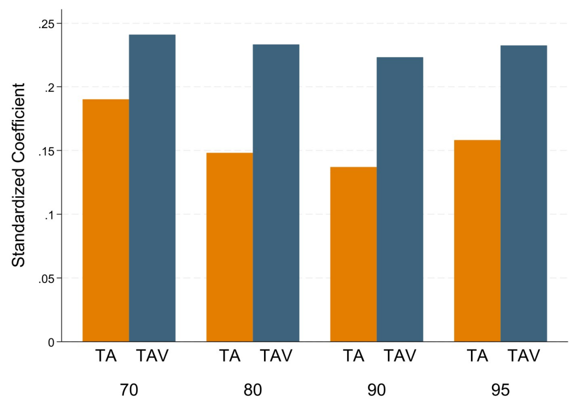
Figure 7: Capturing dynamics at both tails of the distribution



This figure displays the standardized coefficients of TA (orange) and TAV (blue), derived from regression analysis where the number of extreme days in a month and state is regressed on both TA and TAV. The coefficients are then "standardized" by multiplying each by their respective metrics' standard deviation. We define extremes by calculating historical (1960–2004) percentile pairs of temperature anomalies for each state and month: the 5th and 95th percentiles, the 10th and 90th percentiles, the 20th and 80th percentiles, and the 30th and 70th percentiles. These pairs represent the extremes of both tails of the temperature anomaly distribution. The percentile thresholds are then used to compute the number of realized extreme days in a month from 2005 through 2019 for each state. This graph reports the coefficients on TA and TAV of the regression $y_{s,[m,y]} = \beta \cdot \mathrm{TA}_{s,[m,y]}$ and $y_{s,[m,y]} = \beta \cdot \mathrm{TAV}_{s,[m,y]}$, where y is the number of extreme temperature days based on the percentile pairs for each unique combination of month, year, and state (m, y, s). The coefficients highlight that TAV more effectively captures the incidence of extreme temperatures than TA does. This is consistent across all combined percentile ranges, illustrating $TAV's$ ability to account for both cold (lower percentiles) and hot (higher percentiles) extremes.

on surpassing any of the four given percentiles, on TA and TAV. Figure 8 presents the standardized coefficients of TA and TAV, which denote the magnitude of their respective relationships with temperature intensity. The results indicate that a one-standard deviation increase in TAV corresponds to an approximately 0.25 degree rise in the temperature anomaly. In contrast, a one-standard deviation increase in TA is associated with roughly a 0.15 degree increase. The results therefore suggest that changes in variability are also better than changes in the mean at capturing the changing intensity of extreme temperatures.

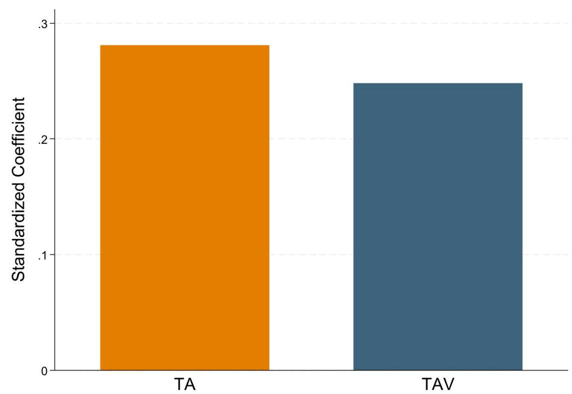
Figure 8: Intensity of extreme hot temperatures



This figure displays the magnitude of the relationship between the intensity of hotter than normal temperatures to TA (orange) and TAV (blue). These standardized coefficients are derived from a regression analysis where the mean temperature anomaly, conditional on days exceeding a specified percentile threshold for that month, is regressed on both TA and TAV. The coefficients are then standardized by multiplying each by their respective metrics' standard deviation. We define extremes by calculating historical (1960–2004) percentiles of temperature anomalies for each state and month: the 70th, 80th, 90th, and 95th percentiles. The percentiles represent the extremes at the right tail of the temperature anomaly distribution, indicating hotter than normal temperatures. The percentile thresholds are then used to compute the average temperature anomaly in a month for the days exceeding the threshold—a measure of temperature intensity. This graph reports the coefficients on TA and TAV of the regression $y_{s,[m,y]} = \beta \cdot \mathrm{TA}_{s,[m,y]}$ and $y_{s,[m,y]} = \beta \cdot \mathrm{TAV}_{s,[m,y]}$, where y is the average temperature anomaly for each unique combination of month, year, and state (m, y, s). The coefficients suggest TAV more effectively represents intense temperatures relative to TA.

As an additional test, we follow Pankratz et al. (2023) and Addoum et al. (2020) to categorize extremes as temperatures above a 30°C threshold. To obtain temperature data—not anomalies, in this case—we use the the nClimGrid-Daily product from the National Oceanic and Atmospheric Administration, which consists of daily gridded fields and area averages of maximum temperatures for the contiguous United States. For each month we calculate the number of days exceeding the 30°C threshold for each state between 2005 and 2019. We then regress the number of days that exceed the threshold on TA and TAV along with month fixed effects to control for seasonality. Figure 9 presents the standardized coefficients of TAV (blue) and TA (orange) in capturing the number of days above 30°C. The results demonstrate a similar capability of TAV and TA in representing these right-tail temperature extremes.

Figure 9: Capturing number of days above 30°C



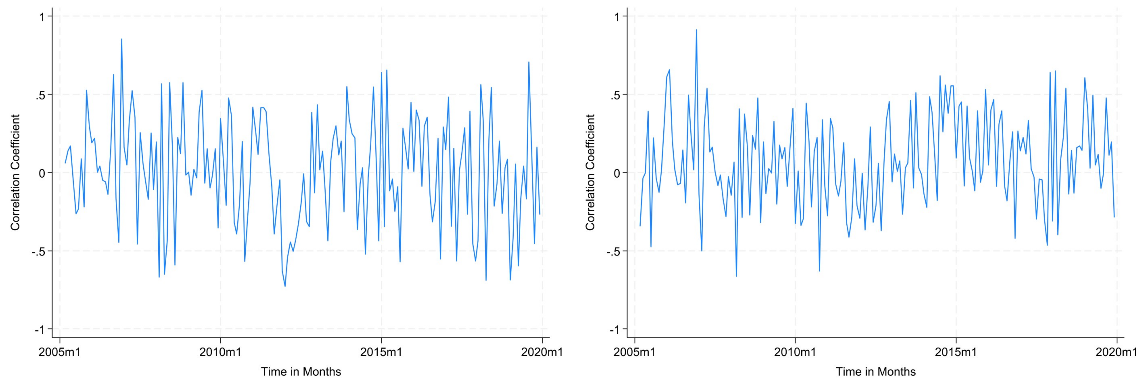
This figure displays the magnitude of the relationship between the number of days in a month over 30°C in a state to TA (orange) and TAV (blue). The standardized coefficients are derived from a regression analysis where the number of days exceeding the threshold in a month are regressed on both TA and TAV. The coefficients are then standardized by multiplying each by their respective metrics' standard deviation. This graph reports the coefficients on TA and TAV of the regression $y_{s,[m,y]} = \beta_1 \cdot \text{TA}_{s,[m,y]} + \beta_2 \cdot \text{TAV}_{s,[m,y]} + \omega$, where y is the number of days above 30°C per month, year, and state (m, y, s). ω represents a set of month fixed effects.

A.4 Correlation between TAV and TA

Using a panel of TA and TAV values for each state, we calculate the correlation coefficient between the two metrics across all states for each month. Panel (a) of Figure 10 plots the monthly correlation between TA and TAV over the sample period, which generally ranges from 0.5 to -0.5, with an average correlation of 0.076 across the entire sample period. This suggests no consistent relationship between the two metrics, indicating they represent distinct sets of information. These results are consistent across different frequencies, such as quarterly and yearly, as shown in Panels (a) and (b) of Figure 11. In Panel (b) of Figure 10, we use the absolute value of TA, equating colder-than-normal temperatures with abnormal heat.

Figure 10: Monthly correlation between TA and TAV

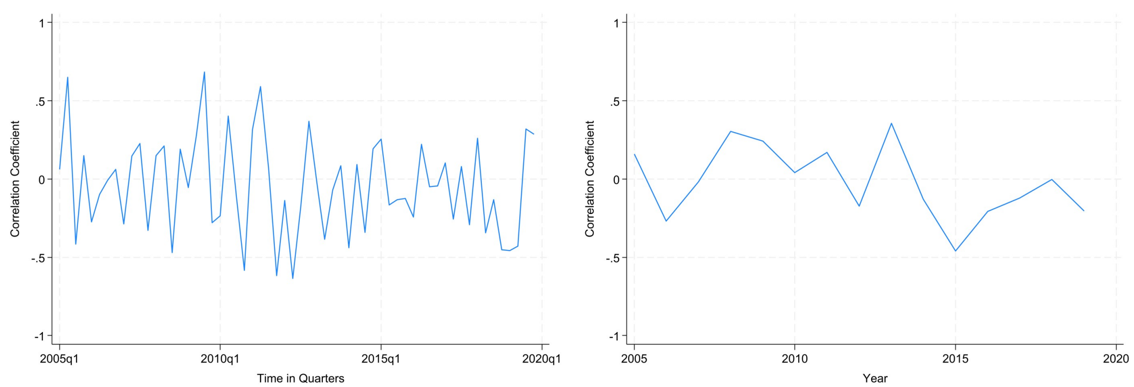
(a) Correlation of TA and TAV (b) Correlation of $|TA|$ and TAV



This figure presents the monthly correlation between TA and TAV (panel a) and $|TA|$ and TAV (panel b) from 2005 to 2019.

Figure 11: Correlation between TA and TAV

(a) Quarterly (b) Yearly



This figure presents the quarterly (panel a) and yearly (panel b) correlation between TA and TAV from 2005 to 2019.

Online appendix to “Volatile Temperatures and their Effects on Equity Returns and Firm Performance”

B Appendix B - Validation of TAV

We further validate the TAV measure using additional empirical tests to understand the drivers of the results in our asset pricing and profitability tests. Realistically, two mechanisms, in addition to attention, could influence our main empirical results: fluctuating consumer demand and supply side effects. The first set of exercises uses various datasets, including the US Consumer Expenditure Survey and electricity consumption records, to find that aggregate demand decreases with TAV, although with industry-specific caveats. The second set uses data from the American Time Use Survey and US Labor Statistics to show that workers in temperature-sensitive industries decrease their minutes worked with greater TAV.

B.0.1 Temperature and consumption

Recent literature has begun to investigate the effects of temperature on household consumption (Roth Tran (2023) and Lee and Zheng (2024)) and electricity demand (Zachariadis and Pashourtidou (2007) and Chang et al. (2016)), documenting a moderate impact of extreme temperatures on consumer behavior and a significant sensitivity of electricity demand to temperature. In this section, we leverage our metrics once again to re-examine the relationship between temperature and consumer expenditure, as well as between temperature and electricity demand. By doing so, we aim to validate the significance of TAV in explaining how varying temperature conditions influence consumption patterns.

B.0.2 Consumer expenditure

We collect data from the Consumer Expenditure Survey (CEX) from 2005 to 2019. CEX comprises of a rotating panel of households representative of the non-institutionalized US population. The data reflects granular details on consumption expenditures as well as demographic information on household members, including age, education, and salary. In our analysis, we use the FMLI files, which offer details on households such as size and state of residence, and encompass aggregate expenditure variables such as spending on apparel or electricity. Each household, referred to as a consumer unit, undergoes an interview up to four times at three-month intervals, detailing its expenditures from the previous three months. The representative sample, along with the broad set of variables on expenses, income, and demographic characteristics, is an ideal setting to test consumer demand dynamics.

Our sample construction excludes households residing in student housing and those with household members younger than 21 or older than 85 years. This selection criterion leads to approximately 26,000 household interviews per annum across 41 states, though this number declined to 18,852 interviews in 2019. The data on expenditures for the three months preceding each interview was created by aggregating current-quarter and past-quarter expenditure data across various categories—non-durables, durables, utilities, electricity, healthcare, entertainment, and apparel—as outlined in Table 10. These expenditure categories, after being log transformed, serve as the primary dependent variables in our empirical tests, following the specification:

$$Expenditure_{h,s,t} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * TA_{s,t} + \rho_t + \gamma_s + \omega * X_h + \epsilon_{h,s,t}, \qquad (10)$$

where $Expenditure$ represents the log expenditure category for the three months preceding the interview period t, for household h, in state s. The temperature variables, TAV and TA, capture the temperature conditions over the preceding three months in state s. The vector X includes household-specific continuous covariates, which are detailed in Table 11, and variables such as the age of the respondent, the number of rooms in the household, total household income, monthly rent, and family size. Additionally, categorical controls incorporate variables on household composition by earners, marital status, education level, race, urban or rural status, and housing tenure. To mitigate the influence of outliers, each control and expenditure variable is winsorized at the 1% level. Year fixed effects and a rolling three months fixed effect are represented by ρ_t. If an interview is conducted in January or February, we set the year fixed effect to correspond to the previous year. State-level fixed effects, represented by γ_s, control for state-specific characteristics. The specification focuses on the variation within states over time, with state-level clustering used to account for treatment effects.

Table 10: Expenditure categories and their corresponding FMLI variables

Expenditure Categories	FMLI Variables
Total Expenditure	totexp
Non-durable Goods	fdhome + fdxmap + alcbev + gasmo + pubtra + persca + tobacc + misc
Durable Goods	houseq + cartkn + cartku
Health Care	health
Electricity	elctrc
Utilities	ntlgas + elctrc + allful + teleph + watrps
Entertainment	entert
Apparel	menboys + womgrl + chldrn + footwr + othapl

This table presents the household expenditure categories in the US Consumer Expenditure Survey. During the interview, a consumer unit (household) is asked to report their expenditures, and the names of the recorded expenditure categories are presented as FMLI variables in the right-hand column. These are grouped into broader expenditure categories in the left-hand column.

Table 12 presents the results from the panel regressions for each expenditure category. The first column reveals that a one-standard-deviation increase in TAV is followed by a notable 0.26% reduction in total expenditure, whereas TA does not have a significant effect on total expenditures. For scale, an additional household member correlates with a 3% increase in expenditures over the prior three months. Taking Texas as an example, these estimates suggest that the average household in that state, with yearly expenditures around $51,368, would reduce spending by approximately $134 per year. For the 24,921 surveyed households in Texas, this implies a potential aggregate expenditure decrease of over $3 million per year for every one-standard deviation increase in TAV. Extrapolating these estimates to the nearly 10 million households in Texas as of 2019, according to the US Census Bureau, this implies an annual expenditure reduction of over $1 billion under similar deviations in temperature variability.

Consistent with our findings in Section 4, we observe substantial heterogeneity across expenditure categories. Specifically, there is a significant positive relationship between TAV and utility and electricity spending, paralleling the positive effect of TAV on profitability observed in our industry-level analysis. This result suggests that households' sensitivity

Table 11: Control variables for consumer expenditure regressions

Controls	FMLI Name	Categorical or Continuous
Age	age_ref	
Number of rooms	roomsq	
Income from salary or wages	fsalarym	Continuous
Monthly rent	renteqvx	
Family size	fam_size	
Composition of earners	earncomp	
Marital status	marital1	
Education	educ_ref	
Race	ref_race	Categorical
Urban or rural	bls_urbn	
Housing tenure	cutenure	

This table presents consumer-unit-specific control variables obtained from the US Consumer Expenditure Survey. These variables are used as controls in Specification 10.

Table 12: Household expenditure sensitivity to temperature

	(1) Tot Exp	(2) Non-Durbl	(3) Durbl	(4) Util	(5) Elect	(6) Hlth Care	(7) Enter	(8) Appar
TAV	-0.003**	-0.004**	-0.009**	0.007**	0.009**	-0.002	-0.004	-0.006**
	(-2.104)	(-2.225)	(-2.306)	(2.492)	(2.552)	(-0.711)	(-1.562)	(-2.024)
TA	-0.001	0.001	-0.001	-0.004***	-0.002	0.001	0.000	0.003**
	(-1.537)	(1.173)	(-0.564)	(-5.738)	(-1.289)	(0.442)	(0.006)	(2.480)
Constant	8.458***	7.293***	5.616***	6.172***	5.123***	5.068***	5.114***	4.464***
	(215.426)	(179.853)	(76.983)	(105.520)	(91.450)	(43.382)	(78.467)	(55.396)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Yr Quart FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Sq	0.527	0.382	0.163	0.277	0.239	0.159	0.185	0.174
Obs	248231	248128	237130	247917	244316	218975	232237	186788

This table presents regressions relating TAV and TA to household expenditures, as obtained from the US Consumer Expenditure Survey from 2005 to 2019. The dependent variables are the log-transformed expenditure variables of each consumer unit (household) and are described in detail in Table 10. Control variables include the age of the interviewee, number of rooms in the household, income, monthly rent, family size, number of earners, marital status of the interviewee, education level, race, urban or rural living, and housing tenure. All specifications include year, month, and state fixed effects. Standard errors are clustered at the state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels and are indicated by ***, **, and *, respectively.

to temperature variability increases their electricity and heating expenditures to manage indoor temperatures, leading to higher revenues for utility providers. Conversely, increased TA correlates with reduced utility usage, mirroring the observed decline in returns during periods of higher-than-usual temperatures in our stock price analysis. Crucially, Table 12 reports a negative relationship between TAV and expenditures in categories such as non-durables, durables, and apparel. These findings are directionally consistent with our results in Section 4.3, which indicate widespread declines in cash flows across sectors, particularly within the durables industry.

Each of these findings suggests a demand channel influencing the consumption decisions of affected households. We argue that these results present compelling evidence that TAV effectively captures how varying temperature conditions influence consumption patterns. When examining the aggregate impacts across states, the total dollar value loss in consumption proves to be substantial. This strongly suggests that changes in TAV materially reduce total household expenditures, with significant heterogeneity across expenditure categories. This result substantially extends the work by Addoum et al. (2023), which documents a 5% reduction in foot traffic for hotels, restaurants, and recreational establishments during the months of April through June. Moreover, the aggregate reduction in household consumption corroborates the findings of Roth Tran (2023), which indicate that increases in online sales during weather shocks fail to fully compensate for the decreases in in-store sales. Unlike prior studies that highlight specific impacts, our findings demonstrate that TAV influences consumption patterns across most categories. This broad applicability underscores the utility of TAV for assessing firms' exposure to temperature variability across various industries. As argued in Section 5, incorporating TAV into climate risk reporting will allow investors to better understand the potential financial impacts of temperature fluctuations on their stock investments.

B.0.3 Electricity consumption

Temperature impacts electricity demand. Previous studies provide empirical evidence on the effects of temperature shocks on electricity consumption (Burke et al. (2015), **?** and Lucidi et al. (2024)). We consider this well-established relationship and investigate whether unexpected changes in electricity demand are more influenced by deviations in temperature variability or by mean temperature anomalies, thereby once again validating TAV's role in explaining unexpected changes in electricity consumption patterns.

We source monthly energy consumption data for all 50 US states from the US Energy Information Administration, covering the period from September 1990 to December 2020. In the US, energy consumption is classified into four end-use sectors: 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 transportation. Due to the strong seasonal patterns in energy consumption, our analysis focuses on modeling short-run temperature effects that are not captured by long-term trend analysis (Son and Kim (2017)). We link the observed seasonality of monthly energy demand to two temperature components: anomalies and deviations in variability (Bigerna (2018)). Following Bigerna (2018), we run an ARMA(J,P) model for each state s:

$$Q_{s,t} = \sum_{j=1}^{J} a_j Q_{t-j} + \sum_{p=1}^{P} b_p \epsilon_{t-p} + \epsilon_{s,t} \tag{11}$$

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. Next, we regress the residuals against TA and TAV, respectively, and estimate a fixed effects model:

$$\epsilon_t = \beta_1 * TAV + \beta_2 * TA + \gamma_t + \eta_n + \varepsilon_t. \tag{12}$$

The estimation results are reported in Table 13. TAV significantly accounts for the unexplained changes in the ARMA process for the residential and industrial sectors, as well as in the overall aggregate analysis. An increase in deviations of the temperature anomaly from the norm, like more frequent heatwaves or cold snaps, leads to a rise in energy demand. Greater temperature variability implies greater uncertainty about electricity demand. Consequently, the forecast value of electricity consumption exhibits a larger error—larger unpredictable change in demand—relative to the best-fit value estimated through Expression (11). Our findings suggest that this error is inherently determined by the extent of the temperature variability. The non-significant coefficient estimation for TAV in the commercial sector suggests that the elasticity of electricity consumption differs between the residential and commercial sectors. This is supported by Zachariadis and Pashourtidou (2007), who found that the residential sector is highly reactive to weather conditions, as demand in the short term is inelastic to price. Thus, our findings confirm a demand channel where temperature variability influences electricity consumption, supporting the notion that energy use is highly affected by weather conditions (Quayle and Diaz (1980)) and sensitive to significant shifts in temperature variation (Chang et al. (2016)).

Table 13: Estimation Results for energy consumption

	Residential	Commercial	Industrial	Total
TAV	0.0054***	0.0006	0.0020**	0.0025***
	(0.0011)	(0.0006)	(0.0009)	(0.0005)
TA	-0.0011	0.0013**	0.0004	0.0002
	(0.0008)	(0.0006)	(0.0004)	(0.0006)
State 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

This Table presents the estimated coefficient for equation $\epsilon_t = \beta_v * TAV + \beta_t * TA + \gamma_t + \eta_n + \varepsilon_t$ 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. The sample period is 2005-2020 for the 50 US states. TA and TAV are the state level temperature measures. Standard errors, presented in parenthesis are clustered both at state and time levels. Statistical significance is calculated at the 1%, 5%, and 10% levels and are indicated by ***, **, *, respectively.

B.1 Temperature and production: Labor hours worked

Severe temperature conditions, such as warmer-than-normal or colder-than-normal days, can increase the discomfort individuals experience during working hours, significantly impacting labor supply. Prior studies by Graff Zivin and Neidell (2014) and Neidell et al. (2021) offer empirical evidence on the effects of extremely high temperatures on labor. However, temperature anomalies in both tails of the distribution can cause physical discomfort and affect the amount of work people perform. Here, we leverage our metrics to re-examine the relationship between temperature and the average weekly hours worked per month, validating the significance of TAV in explaining how varying temperature conditions affect labor supply.

We begin by analyzing the average weekly hours worked in a month relative to TAV and TA. We obtain the work data from the Federal Reserve Bank (FED) of St Louis for the categories: construction, manufacturing for durable goods, manufacturing for non-durable goods, leisure and hospitality, trade, transportation, utilities, financial activities, and other services. The data is available at a monthly frequency for various states and categories. We regress the average weekly minutes worked at the state level on TAV and TA along with the US-level unemployment rate, the FED funds rate, and the change in the Consumer Price Index (CPI). We select data from 2010 onwards because the majority of the data starts only in 2007, and the period from 2007 to 2009 was influenced by the global financial crisis. To control for state-level economic trends and job seasonality across states, we apply state-by-year-by-quarter fixed effects. This approach ensures that the primary remaining variation is within-quarter monthly variation. We conduct panel unit root tests to show that weekly minutes are indeed stationary.

The first column of Table 14 presents the results from the regressions, showing that a one-unit increase reduces average work times across all industries by about 3 minutes per week. This is remarkably close the Neidell et al. (2021), who find that during periods of economic growth, for every degree above 90° Fahrenheit (∼32°C) on a particular day, the average high-risk worker reduces their work time by approximately 2.6 minutes, relative to a 90°F day. Of course, the impact varies across sectors, with the construction industry experiencing the most severe negative effects, losing more than 8 minutes per week. The manufacturing of durable goods and the leisure and hospitality sectors are also negatively impacted.

TA, on the other hand, is positive for construction, durables, and hospitality sectors, meaning that abnormally hotter temperatures in the US lead to increased work time. A one standard deviation rise in TA leads to about a 2-minute increase in durable goods manufacturing. One reason for this could be that TA captures extremes in the 70th percentile of hot extremes. The slight increase suggests that slightly hotter temperatures may allow for more work time, especially in the construction and hospitality industries.

For our second analysis, we use the American Time Use Survey Data, a nationally representative cross-sectional survey that documents how Americans aged 15 and over allocate their time. Respondents provide a detailed diary of their activities, locations, and the duration of each activity (down to the minute) for the preceding 24 hours. Our analysis follows the methodology outlined in Graff Zivin and Neidell (2014) and Neidell et al. (2021) in defining the total hours devoted to work during the day before the interview.

Table 14: Average weekly minutes worked and temperature variations

	(1) All	(2) Const	(3) Dur	(4) Non-Dur	(5) Hospitality	(6) Trade	(7) Fin	(8) Serve
TAV	-2.947*	-8.375***	-5.261**	-2.145	-4.147***	-0.261	2.191	-2.868
	(1.791)	(3.224)	(2.130)	(2.425)	(1.481)	(1.102)	(1.763)	(1.978)
TA	0.257	0.921***	0.479***	0.244	0.255**	0.051	-0.161	-0.054
	(0.161)	(0.256)	(0.178)	(0.229)	(0.130)	(0.087)	(0.157)	(0.175)
UNRATE	-10.627**	3.360	-34.816***	-21.631***	-1.972	-21.598***	-1.348	3.139
	(4.870)	(7.454)	(5.153)	(6.826)	(3.970)	(2.733)	(4.694)	(5.167)
FEDFUNDS	-21.454*	10.576	17.021	-15.705	23.320***	-17.022***	-142.716***	-39.740***
	(11.068)	(17.826)	(14.029)	(16.834)	(8.460)	(5.732)	(9.190)	(11.639)
CPI	0.353	-2.450	-1.317	0.196	1.835**	0.327	2.193**	1.704
	(0.992)	(1.563)	(1.196)	(1.450)	(0.865)	(0.574)	(0.968)	(1.081)
Constant	2191.532***	2299.638***	2707.722***	2576.746***	1531.305***	2197.519***	2321.615***	1873.095***
	(30.954)	(46.930)	(33.111)	(43.142)	(24.662)	(17.254)	(29.407)	(32.672)
StatexYrxQ	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	No	No	No	No	No	No	No
ADJ R2	0.932	0.843	0.873	0.856	0.919	0.910	0.696	0.936
Observations	34200	5160	4560	3960	6000	6000	4920	3600

This table presents results associating the weekly minutes worked in different industries at the US state level to TA and TAV. The average weekly minutes worked at a monthly frequency for certain states is obtained from the US Bureau of Labor Statistics and the Federal Reserve Bank of St. Louis database. Const represents the construction industry, Dur stands for durables, Non-Dur refers to non-durables, Fin denotes finance, and Serve represents the services industry. UNRATE and CPI are the state-level unemployment rate and consumer price index at the monthly frequency, respectively. FEDFUNDS represents the Federal Funds Rate at the monthly frequency. Regressions contain state-by-year-by-quarter fixed effects or industry-level fixed effects. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels and are indicated by ***, **, and *, respectively.

We follow Graff Zivin and Neidell (2014) in obtaining individual-level demographic data and identify high-risk workers as those in agriculture, forestry, fishing, hunting, mining, construction, manufacturing, transport and utilities sectors (23% of the data). The remaining industries—wholesale and retail trade, information, professional and business services, educational and health services, leisure and hospitality, other services, and public administration—as low risk (76% of the data). Furthermore, we follow Graff Zivin and Neidell (2014) in defining a categorical variable equal to 1 for workers in a "high-risk" industry, and 0 for workers in a "low-risk" industry.

Table 15 presents estimates from regressing the hours worked during the day prior to the interview on an interaction between the temperature variables in the interviewee's state, and whether the worker is in a high-risk industry. The regression includes a comprehensive set of demographic controls, such as income, ethnicity, education, age, children, and marriage status. Additionally, we include state-by-year-by-quarter fixed effects to control for state-level economic variables and industry-by-year fixed effects to control for technological innovation within each industry. Overall, the results indicate that a worker in a high-risk industry works approximately 3.2 fewer minutes for each one-unit increase in TAV compared to a worker in a low-risk industry. This once again confirms Neidell et al. (2021), who report that for every degree above 90°F on a given day, the average high-risk worker reduces their work time by about 2.6 minutes relative to a 90°F day. However, unlike Neidell et al. (2021), we observe that the effect is consistent across different periods, regardless of economic growth.

Table 15: Minutes worked on the prior day

	(1) 2005-2019	(2) 2005-2019	(3) 2007-2014	(4) 2005-2019	(5) 2007-2014
Highrisk × TAV	-3.264**	-2.845**	-3.192*	-2.845**	-3.192*
	(1.252)	(1.309)	(1.683)	(1.309)	(1.683)
Highrisk × TA	0.370	0.432	0.510	0.432	0.510
	(0.539)	(0.560)	(0.694)	(0.560)	(0.694)
Constant	-5.820	-5.862	-2.339	-5.862	-2.339
	(5.810)	(5.981)	(7.920)	(5.981)	(7.920)
Controls	Yes	Yes	Yes	Yes	Yes
IndxYear	Yes	Yes	Yes	Yes	Yes
StatexYrxQ	No	Yes	Yes	Yes	Yes
Adj R Squared	0.345	0.346	0.338	0.346	0.338
Observations	108029	108012	60996	108012	60996

This table presents results associating the minutes worked on the previous day to TAV and TA. The first two rows represent the interaction between individuals working in a high-risk industry and the temperature metrics in the state where the respondent resides. We use American Time Use Survey Data to measure the number of minutes the respondent worked on the previous day. We follow Graff Zivin and Neidell (2014) in obtaining individual-level demographic data and identify workers in high-risk industries: agriculture, forestry, fishing, hunting, mining, construction, manufacturing, transport, and utilities sectors (23% of the data). The remaining industries—wholesale and retail trade, information, professional and business services, educational and health services, leisure and hospitality, other services, and public administration—are classified as low risk (76% of the data). The categorical variable Highrisk equals 1 for workers in a "high-risk" industries, and 0 for workers in "low-risk" industries. Control variables include the age of the respondent, whether they are married and cohabitating, education, race, income, employment, sex, and the day of the week of the interview. Fixed effects include industry-by-year and state-by-year-by-quarter. Standard errors are clustered at the state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels and are indicated by ***, **, and *, respectively.

C Appendix C

We conduct additional empirical tests to check the robustness of our main results.

C.1 Long-short portfolio robustness checks

C.1.1 Absolute value of TA

In our cross-sectional asset pricing tests, we use the values of TA to differentiate firms experiencing abnormally cold and hot months. Here, we use the absolute value of TA to interpret abnormally cold or hot months as equally damaging to firm returns. Sorting states in this manner, we place those firms experiencing extreme cold or hot temperatures in the first TA quintile (Portfolio 1) and those enjoying similar temperature patterns to historical averages in the fifth quintile (Portfolio 5). Table 16 shows that there is no statistical difference in portfolio returns when treating hot and cold temperatures similarly.

Table 16: Abnormal returns to portfolios sorted on $|TA|$

	Portfolios sorted on $\|TA\|$			
	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.850***	0.139	0.111	0.159*
	(0.010)	(0.112)	(0.233)	(0.070)
Portfolios 2,3,4	0.729**	0.070	0.041	0.058
	(0.023)	(0.162)	(0.412)	(0.207)
Portfolio 5	0.850***	0.179	0.143	0.139
	(0.008)	(0.103)	(0.208)	(0.210)
Portfolio 1 - 5	0.000	-0.041	-0.032	0.020
	(0.998)	(0.798)	(0.846)	(0.898)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the absolute value of the mean of temperature anomalies $|TA|$. Each month t, we sort US states into five groups (quintiles) based on their realization of $|TA|$. The returns of the firms headquartered in these groups of states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing similar average temperatures to historical periods. Portfolio 5 includes those firms in states experiencing the highest values of $|TA|$ (warmest or coldest states). We group the middle three portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factors and liquidity factor, and the Fama-French 5 factors, respectively. "Portfolio 1–5" reports the return spread between Portfolios 1 and 5 (i.e., the return difference between the least and most exposed portfolios). To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated within the US. The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are given in parentheses and are calculated using the Newey-West correction for 6 lags.

C.1.2 Different geographic concentration thresholds

We further examine the robustness of our results by adjusting the criteria for geographic concentration and the percentage of international revenue. We use the variables $nearstate$ and the percentage of income earned abroad as two levers for assessing the robustness of our main cross-sectional results.

First, we raise the threshold for income earned domestically to 80%, focusing on firms whose revenue is more dependent on domestic temperature conditions. We keep firms with a more geographically concentrated operational footprint by selecting a $nearstate$ value of 8.2%. Table 17 reports the results. The abnormal returns remain significant and are greater by 4 basis points than our baseline cross-sectional results in Section 4.2. As a reminder, the baseline included firms that mentioned their headquartered state no more than 8.2% of the time compared to all other states in their 10-K filings and those with more than 65% of revenues from the US. In a second exercise, we keep firms that mention their headquartered state more than 14.1% of the time (20th percentile) compared to all mentioned US states in their 10-K filings and those with more than 65% of revenues from within the US. Table 18 reports the results. This new sorting creates a TAV portfolio that earns an additional 2.4 basis points compared to the baseline results. Next, we consider the extreme geographic concentration case. We set higher thresholds for both variables, including only those firms that mention their headquartered state in 15% of all state mentions in their 10-K filings and those with more than 80% of revenues from within the US. Table 19 reports the results, showing a greater return of 9 basis points compared to baseline.

In all these cases, higher geographic concentration or greater dependence on domestic revenues strengthens the effect of temperature variability on excess returns. Conversely, relaxing the criteria diminishes the effect, confirming that our identification strategy is working as intended. This is evident when considering firms with only 30% of their income earned domestically and firms that mention their headquartered state no more than 4% of the time relative to all mentioned US states in their 10-K filings. Table 20 reports the results. Sorting states using this less stringent threshold yields a decrease of 11.5 basis points compared to the baseline, after controlling for the Fama-French 5 factors.

Table 17: Abnormal returns to portfolios sorted on temperature metrics: more geographically concentrated firms

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.712*	0.011	0.023	0.045
	(0.057)	(0.930)	(0.856)	(0.694)
Portfolios 2,3,4	0.674**	0.021	0.006	0.014
	(0.044)	(0.724)	(0.932)	(0.787)
Portfolio 5	0.900***	0.258**	0.210*	0.236*
	(0.004)	(0.047)	(0.085)	(0.096)
Portfolio 1 - 5	-0.188	-0.247	-0.186	-0.191
	(0.325)	(0.193)	(0.326)	(0.338)

Panel B: Portfolios sorted on TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.057***	0.382***	0.411***	0.351***
	(0.001)	(0.000)	(0.002)	(0.001)
Portfolios 2,3,4	0.665**	0.021	-0.019	0.005
	(0.039)	(0.752)	(0.753)	(0.944)
Portfolio 5	0.652*	-0.095	-0.110	-0.078
	(0.090)	(0.319)	(0.291)	(0.409)
Portfolio 1 - 5	0.404***	0.476***	0.521***	0.430***
	(0.008)	(0.001)	(0.004)	(0.003)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 80% of their revenues generated within the US. Each month t, we sort US states into five groups (quintiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 5 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle three portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors, respectively. "Portfolio 1–5" reports the return spread between portfolios 1 and 5 (i.e., the return difference between the least and most exposed portfolios). The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 18: Abnormal returns to portfolios sorted on temperature metrics: more geographically concentrated firms

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.820**	0.127	0.110	0.112
	(0.012)	(0.272)	(0.336)	(0.302)
Portfolios 2,3,4	0.682**	0.026	-0.006	-0.006
	(0.028)	(0.616)	(0.915)	(0.890)
Portfolio 5	0.919***	0.247*	0.223	0.210
	(0.003)	(0.058)	(0.113)	(0.116)
Portfolio 1 - 5	-0.098	-0.120	-0.113	-0.098
	(0.598)	(0.516)	(0.574)	(0.608)

Panel B: Portfolios sorted on TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.097***	0.400***	0.418***	0.348**
	(0.000)	(0.003)	(0.007)	(0.010)
Portfolios 2,3,4	0.688**	0.038	-0.032	-0.005
	(0.019)	(0.532)	(0.538)	(0.931)
Portfolio 5	0.670*	-0.062	-0.036	-0.054
	(0.067)	(0.514)	(0.703)	(0.559)
Portfolio 1 - 5	0.427**	0.463**	0.455**	0.402**
	(0.014)	(0.012)	(0.016)	(0.029)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). To control for operational dispersion, we select firms that mention their headquartered state at least 14.1% of the time (the 20th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated within the US. Each month t, we sort US states into five groups (quintiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 5 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle three portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors, respecitvely. "Portfolio 1–5" reports the return spread between portfolios 1 and 5 (i.e., the return difference between the least and most exposed portfolios). The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 19: Abnormal returns to portfolios sorted on temperature metrics: more geographically concentrated firms

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.730**	0.039	0.041	0.025
	(0.035)	(0.778)	(0.761)	(0.850)
Portfolios 2,3,4	0.668**	0.019	-0.002	-0.006
	(0.039)	(0.753)	(0.981)	(0.915)
Portfolio 5	0.886***	0.217*	0.200	0.200
	(0.007)	(0.084)	(0.149)	(0.132)
Portfolio 1 - 5	-0.157	-0.178	-0.159	-0.175
	(0.435)	(0.379)	(0.458)	(0.410)

Panel B: Portfolios sorted on TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.101***	0.409***	0.436***	0.364***
	(0.000)	(0.001)	(0.007)	(0.003)
Portfolios 2,3,4	0.681**	0.038	-0.019	-0.001
	(0.024)	(0.538)	(0.727)	(0.990)
Portfolio 5	0.639*	-0.094	-0.108	-0.075
	(0.091)	(0.351)	(0.316)	(0.444)
Portfolio 1 - 5	0.462***	0.503***	0.544**	0.439**
	(0.007)	(0.004)	(0.011)	(0.012)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). To control for operational dispersion, we select firms that mention their headquartered state at least 15% of the time in their 10-K filings, compared to mentions of all other states, and firms with more than 80% of their revenues generated in the US. Each month t, we sort US states into five groups (quintiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 5 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle three portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors, respectively. "Portfolio 1–5" reports the return spread between portfolios 1 and 5 (i.e., the return difference between the least and most exposed portfolios). The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 20: Abnormal returns to portfolios sorted on temperature metrics: less geographically concentrated firms

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.913***	0.203**	0.181*	0.222**
	(0.008)	(0.044)	(0.099)	(0.023)
Portfolios 2,3,4	0.688**	0.009	-0.004	-0.015
	(0.035)	(0.857)	(0.941)	(0.743)
Portfolio 5	0.900***	0.227*	0.179	0.197
	(0.005)	(0.055)	(0.119)	(0.103)
Portfolio 1 - 5	0.013	-0.024	0.002	0.025
	(0.941)	(0.880)	(0.991)	(0.879)

Panel B: Portfolios sorted on TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.038***	0.352***	0.356***	0.319***
	(0.001)	(0.001)	(0.001)	(0.003)
Portfolios 2,3,4	0.704**	0.049	-0.002	0.014
	(0.020)	(0.388)	(0.962)	(0.801)
Portfolio 5	0.755*	-0.012	0.000	0.011
	(0.051)	(0.887)	(0.998)	(0.895)
Portfolio 1 - 5	0.283*	0.364**	0.356**	0.309**
	(0.068)	(0.012)	(0.021)	(0.043)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). To control for operational dispersion, we select firms that mention their headquartered state at least 4% of the time (the 5th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 40% of their revenues generated in the US. Each month t, we sort US states into five groups (quintiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 5 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle three portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors, respectively. "Portfolio 1–5" reports the return spread between portfolios 1 and 5 (i.e., the return difference between the least and most exposed portfolios). The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

C.1.3 Six and four portfolio sorts

We also conduct our portfolio sorts using sextiles and quartiles to demonstrate that the observed differences in returns persist under a more or less granular sorting method. The results remain consistent, indicating that our findings are not dependent on sorting granularity.

Table 21: Abnormal returns to portfolios sorted on temperature metrics: six sorts

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.817**	0.103	0.090	0.096
	(0.023)	(0.289)	(0.359)	(0.324)
Portfolios 2,3,4,5	0.925**	0.057	0.012	0.047
	(0.027)	(0.344)	(0.869)	(0.377)
Portfolio 6	0.958***	0.285**	0.231*	0.224
	(0.002)	(0.048)	(0.091)	(0.128)
Portfolio 1 - 6	-0.141	-0.182	-0.140	-0.127
	(0.433)	(0.299)	(0.442)	(0.482)

Panel B: Portfolios sorted on TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.075***	0.402***	0.438***	0.347***
	(0.001)	(0.000)	(0.001)	(0.001)
Portfolios 2,3,4,5	0.947**	0.066	0.023	0.059
	(0.025)	(0.320)	(0.736)	(0.400)
Portfolio 6	0.771**	0.051	0.069	0.054
	(0.021)	(0.589)	(0.492)	(0.562)
Portfolio 1-6	0.304**	0.351***	0.369***	0.293**
	(0.025)	(0.009)	(0.009)	(0.030)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). Each month t, we sort US states into six groups (sextiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 6 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle four portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3,4,5". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors, respectively. "Portfolio 1–6" reports the return spread between portfolios 1 and 6 (i.e., the return difference between the least and most exposed portfolios). To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated in the US. The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 22: Abnormal returns to portfolios sorted on temperature metrics: four sorts

Panel A: Portfolios sorted on TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.780**	0.080	0.067	0.100
	(0.023)	(0.346)	(0.468)	(0.222)
Portfolios 2,3	0.729**	0.076	0.058	0.061
	(0.022)	(0.194)	(0.358)	(0.265)
Portfolio 4	0.740**	0.083	0.033	0.067
	(0.011)	(0.503)	(0.772)	(0.592)
Portfolio 1-4	0.040	-0.002	0.034	0.033
	(0.812)	(0.988)	(0.832)	(0.833)

Panel B: Portfolios sorted on TAV

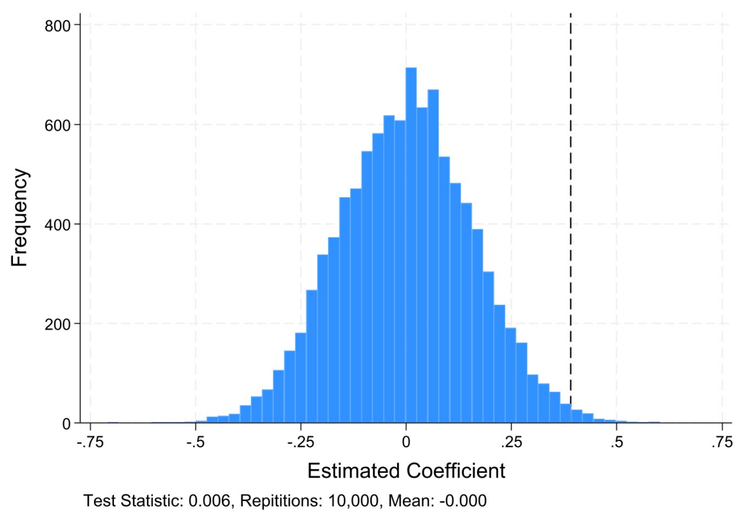
	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.000***	0.322***	0.347***	0.288***
	(0.001)	(0.002)	(0.003)	(0.004)
Portfolios 2,3	0.644**	0.016	-0.067	-0.003
	(0.032)	(0.829)	(0.312)	(0.967)
Portfolio 4	0.667*	-0.065	-0.061	-0.055
	(0.061)	(0.440)	(0.467)	(0.502)
Portfolio 1-4	0.333**	0.387***	0.408***	0.343**
	(0.020)	(0.007)	(0.006)	(0.018)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to either the mean of temperature anomalies (TA, in Panel A) or the standard deviation of temperature anomalies (TAV, in Panel B). Each month t, we sort US states into four groups (quartiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and the lowest values of TAV (low variability). Portfolio 4 includes those firms in states experiencing the highest values of TA (warmer states) and highest values of TAV (high variability). We group the middle two portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors, respectively. "Portfolio 1–4" reports the return spread between portfolios 1 and 4 (i.e., the return difference between the least and most exposed portfolios). To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated in the US. The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

C.1.4 Placebo Tests

To rule out spurious correlations, we conduct placebo tests by randomly assigning states to five different portfolios (quintiles). Using this random allocation for sorting, we then calculate a long-minus-short portfolio and regress the return series on the Fama-French 5 factor model. We repeat this process 10,000 times and present the estimated coefficients in Figure 12. The figure shows a near-normal distribution of coefficients with the actual estimated coefficient in the main specification, 0.391, presented as the vertical dashed line. About 0.6% of the mass of the distribution is greater than 0.391. Overall, the distribution of values indicates that the sorting technique does not inherently produce spurious correlations between temperature and returns, validating the robustness of our main results.

Figure 12: Placebo tests: alpha coefficients after controlling for FF5 factors



This figure presents the coefficients of the excess returns from a long-short methodology that sorts 40 states and the firms headquartered into those states into quintiles based on a random variable with normal distribution, with mean zero and standard deviation of 1. Each month t, we sort US states into five groups (quintiles) based on their realization of either TA or TAV. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. The returns of the portfolio generated by subtracting the 5th quintile from the 1st is regressed on the FF 5 factor model. This process is conducted 10,000 times to produce the alphas presented here. The actual coefficient estimate, 0.391, from our main specification is the vertical dashed line. The test statistic is calculated as the fraction of coefficients from randomized regressions that exceed 0.391.

C.1.5 Transition matrix

We construct a monthly transition matrix to track the movement of states between quintiles over time. Table 23 represents the transition matrix, showing the percentage of times a state transitions from one quintile portfolio to another within our sample period. For instance, in Panel A, the probability of a state remaining in the third quintile of TAV is 28.74%, while the probability of moving from the third quintile to the first quintile is 13.91%. Generally, changes in state sorting occur 10–25% more frequently when the ranking of states is based on their TA rather than TAV. This observation suggests that the autocorrelation of state-level of variability is somewhat greater than TA (i.e., states may be more likely to experience similar levels of variability to the previous period). Nonetheless, the matrix reveals sufficient variation, with states frequently switching from one quintile to another when sorted by either TA or TAV. Moreover, our placebo tests revealed that the sorting methodology is not inherently flawed. This dynamic movement supports the robustness of our sorting methodology and underscores the significance of temperature variability.

C.2 Analyst surprises

We further explore the impact of temperature variability on investor behavior and firm performance. In the main text, we discuss the finding that fluctuations in temperature variability exert a substantial impact on the realized returns of affected companies. Specifically, firms operating in less volatile regions significantly outperform firms operating in more volatile regions. An important question arises: How do specialized analysts react to temperature information? Is there a relationship between TA and TAV and firm-level earnings surprises? Our analysis shows that, on average, a rise in TAV correlates with firms failing to meet analyst expectations of earnings per share.

To explore this, we obtain firm quarterly earnings-per-share surprise data from I/B/E/S and similar performance data from Compustat, as described in Section 4.3. Using a similar specification to expression 5, we adjust only the dependent variable to earnings surprises, which are winsorized at 1%.

Table 24 presents the results where earnings-per-share surprise is multiplied by 100 for

Table 23: Quintile transition matrices

Panel A: TAV

	Rebalanced Quintile 1	2	3	4	5
1	50.00	24.79	13.91	7.70	3.60
2	25.42	31.14	22.88	14.76	5.79
3	14.05	22.88	29.80	21.89	11.37
4	6.50	14.48	21.47	32.84	24.72
5	4.03	6.71	11.94	22.81	54.52
Total	100	100	100	100	100

Panel B: TA

	Rebalanced Quintile 1	2	3	4	5
1	23.88	19.9	17.74	19.06	19.41
2	21.09	21.51	20.39	20.81	16.2
3	18.51	20.11	22.91	19.34	19.13
4	17.32	19.97	20.81	20.74	21.16
5	19.2	18.51	18.16	20.04	24.09
Total	100	100	100	100	100

This table illustrates the frequency of states moving from one quintile of exposure to another. Panel A represents the transition matrix of the portfolio strategy when using TAV and panel B represents TA. The sample period is 2005–2019. The left most column of each panel is the beginning exposure quintile of the state. The other columns represents the exposure quintile of the state in the next month. Each number represents the percent of times a state moves from one quintile to another.

clarity. The first column of the table reveals that earnings per share is reduced by 76 basis points across all firms in the sample. Given that the average firm in the sample has 195 million shares outstanding, a one-standard deviation increase in TAV in a quarter translates to a reduction of $652,000. We find no significant effect of TA on all firms, indicating that temperature variability, rather than average temperature anomalies, plays a critical role in influencing firm performance and investor expectations.

Similar patterns to our industry analysis are also reported in Table 24. Temperature-sensitive industries such as manufacturing and construction all show negative relationships with TAV, indicating that higher temperature variability negatively impacts earnings surprises. Conversely, utilities exhibit a positive surprise, suggesting that increased temperature variability may lead to better-than-expected performance in this sector.

While these results align with our other empirical tests, their implications can be interpreted somewhat differently. The cross-sectional results demonstrated that firms in temperature-stable areas generally overperform, while our tests on investor attention to temperature revealed that investors react significantly to TAV. Together, these findings suggest that the market does respond to TAV. However, analysts seem to underestimate the impact of temperature variability, leading firms to miss earnings targets when TAV rises unexpectedly. This discrepancy indicates a gap between investor behavior and analyst forecasts. Investors react to TAV, likely adjusting their expectations and trading behaviors in response to temperature variability. In contrast, analysts may not fully incorporate the effects of TAV into their earnings projections, resulting in negative earnings surprises for firms in temperature-sensitive industries.

C.3 Temperature and weather derivative pricing

Campbell and Diebold (2005) document that unexpected weather fluctuations can cause substantial pricing effects on the weather derivatives market. Essentially, unforeseen changes in weather conditions create significant uncertainty and difficulty in predicting weather patterns, which is then reflected in the demand and pricing of weather derivatives. We argue that greater temperature variability implies greater uncertainty about the demand for weather protection. This is because higher temperature variability means more frequent and severe extreme temperatures, making it harder for market participants to predict weather patterns. Consequently, this uncertainty drives the demand for weather derivatives.

We now test whether TAV better explains these unexpected weather fluctuations compared to TA, which only measures the average temperature anomaly. To do this, we consider the temperature derivatives market and use weather derivative prices. The significant impact of weather on electricity demand facilitated the creation of this market.[42]

We obtain daily futures prices (end-of-day) from Bloomberg for temperature derivatives traded on the Chicago Mercantile Exchange (CME) covering the period 2005–2020. These contracts provide buyers with insurance 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.[43] These contracts are available for eight geographically diverse cities across the US 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 (2022) and Schlenker and

[42] 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)).

[43] An HDD contract buyer receives payments for cold days, defined as days when the average temperature falls below 65°F (∼18.3°C). On the other hand, a CDD contract buyer receives payments for hot days, defined as days when the average temperature rises above 65°F.

Table 24: Temperature exposure and analyst earnings surprises

	(1) All	(2) BusEq	(3) Chems	(4) Cnstr	(5) Durbl	(6) Enrgy	(7) Hlth	(8) Manuf	(9) Money	(10) NoDur	(11) Other	(12) Shops	(13) Telcm	(14) Trans	(15) Utils
TAV	-0.76**	-0.05	0.83	-6.72**	-0.66	-1.46	0.32	-2.24**	-0.95	-1.03	-3.03***	0.58	1.00	-1.86	2.61
	(-2.25)	(-0.06)	(0.21)	(-2.67)	(-0.61)	(-0.39)	(0.52)	(-2.47)	(-1.25)	(-0.96)	(-3.31)	(0.41)	(1.08)	(-1.70)	(1.21)
TA	0.19	-0.03	1.06*	0.33	0.73	-0.61	0.14	0.38	0.10	0.88**	0.12	-0.31	0.03	1.12*	-1.35**
	(1.67)	(-0.14)	(1.84)	(0.66)	(1.64)	(-1.06)	(0.72)	(1.61)	(0.58)	(2.24)	(0.36)	(-1.37)	(0.10)	(2.06)	(-2.53)
L.Leverage	35.26***	14.80	266.52	45.44	-24.95	-42.92	-1.44	32.75	45.86	78.10***	-19.46	97.11***	-7.49	24.01	571.58***
	(3.41)	(1.08)	(1.58)	(1.50)	(-1.43)	(-1.33)	(-0.22)	(0.93)	(1.55)	(5.82)	(-0.95)	(2.92)	(-0.78)	(1.19)	(4.53)
L.Inv Rate	-14.45***	-9.32***	-109.20	-30.32**	-16.81*	-51.80***	-3.57*	-60.71***	-8.21**	-45.24*	-15.98**	17.48	-6.25	-47.55***	36.03
	(-3.92)	(-3.73)	(-1.60)	(-2.47)	(-1.88)	(-6.32)	(-1.74)	(-4.86)	(-2.12)	(-1.86)	(-2.22)	(1.23)	(-0.63)	(-4.44)	(0.60)
L.BktoMkt	-15.98***	-12.58**	-45.99	-18.43**	-12.74***	-20.91***	-1.95	-26.23***	-15.87***	-26.62*	-28.09***	-18.86**	-4.02	-19.99**	-17.48*
	(-9.51)	(-2.16)	(-1.43)	(-2.74)	(-3.08)	(-5.12)	(-0.79)	(-5.11)	(-5.25)	(-1.89)	(-3.59)	(-2.26)	(-0.78)	(-2.08)	(-2.04)
L.Earn/Shr	-0.91	-1.64	1.17	6.71***	2.56**	-2.17	1.99**	2.60	1.33	-4.03	-2.32	-5.32*	2.76	0.84	-6.73***
	(-0.95)	(-0.66)	(1.46)	(3.94)	(2.83)	(-1.35)	(2.11)	(1.52)	(0.74)	(-0.55)	(-1.38)	(-1.91)	(1.36)	(0.63)	(-3.37)
L.Tobins Q	-2.27***	-1.68	-6.49	0.94	-0.95	-2.75	0.60	-5.04**	-5.86**	-4.56	-7.68**	-2.08	-0.12	-4.33	-12.50
	(-5.15)	(-1.25)	(-0.62)	(0.31)	(-0.74)	(-0.54)	(0.68)	(-2.22)	(-2.41)	(-0.95)	(-2.66)	(-0.64)	(-0.05)	(-0.78)	(-1.58)
L.ROA	2.97	5.26	189.19***	-75.47**	-16.29	179.66*	-7.45	21.18	-5.16	2.46	-24.90	-135.09**	-0.22	50.90	266.07*
	(0.42)	(0.26)	(7.53)	(-2.13)	(-0.72)	(2.35)	(-1.28)	(0.90)	(-0.11)	(0.06)	(-0.86)	(-2.26)	(-0.02)	(0.60)	(1.84)
L.PPE/A	-56.66***	5.09	-196.65	-5.66	-80.62*	45.76	2.87	-28.15	367.71	-8.96	19.07	-204.03***	6.16	28.02	-280.17***
	(-3.40)	(0.21)	(-1.00)	(-0.15)	(-1.76)	(1.59)	(0.16)	(-0.81)	(1.39)	(-0.10)	(0.67)	(-4.11)	(0.36)	(0.73)	(-3.61)
Constant	42.71***	22.62***	11.16	23.91	62.52***	48.27*	-0.74	44.59***	34.09***	28.74	31.77**	82.39***	28.96***	46.39**	60.30*
	(18.73)	(7.59)	(0.85)	(1.62)	(6.20)	(2.29)	(-0.28)	(3.66)	(3.89)	(1.44)	(2.77)	(8.15)	(4.12)	(2.56)	(1.87)
FirmYr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Sq	0.81	0.82	0.64	0.83	0.89	0.84	0.94	0.82	0.82	0.56	0.61	0.74	0.92	0.86	0.33
Obs	58281	8004	1176	2778	1403	1466	6605	5952	10798	3816	3505	5944	1235	2459	3097

This table presents the results of regressing quarterly earnings-per-share surprises on quarterly temperature anomalies (TA) and variability of temperature anomalies (TAV). Earnings-per-share surprises are multiplied by 100 for clarity. The year-ago control variables include leverage, capital investment rate, log book-to-market equity, Tobin's Q, return on assets, capital expenditure, earnings per share, and plant, property, and equipment over total assets, all from the previous quarter. We select firms that mention their headquartered state at least 8.4% of the time relative to all states mentioned in their 10-K filings and firms with more than 65% of revenues within the US. The quarterly sample period is from 2005 to 2019. All specifications include firm-by-year fixed effects. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

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 (Oregon) (PDX).

We hypothesize that, if traders account for temperature variability, TAV should capture more variation in weather derivatives prices than TA. To verify this, akin to Diebold and Rudebusch (2022), we analyze futures contracts offered by the CME. 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 define CDDs and HDDs as:

$$\begin{aligned} CDD_{i,m} &= \textstyle\sum_{d=1}^{D_m} (T_d - T_0)^+ \\ HDD_{i,m} &= \textstyle\sum_{d=1}^{D_m} (T_0 - T_d)^+. \end{aligned} \tag{13}$$

where T_0 is set at 65°F for a contract traded at the CME.

We then regress the monthly average prices for CDDs and HDDs on TA and TAV:

$$\begin{aligned} CDD_{s,m} &= \beta_t T_m + \beta_e TA_t + \beta_v TAV_t + \beta_v \sigma(TA) + \gamma_m + \eta_s + \epsilon \\ HDD_{s,m} &= \alpha + \beta_t T_m + \beta_e TA_t + \beta_v TAV_t + \beta_v \sigma(TA) + \gamma_m + \eta_s + \epsilon, \end{aligned} \tag{14}$$

where T_m is the average daily temperature level minus 65°F, and TA, $\sigma(TA)$, and TAV are defined in Section 3.1; γ_m and η_s are month and state fixed effects, 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 25 reports the estimated coefficients of various temperature drivers. The first and third columns consider only the underlying temperature on which the contract is written, while the second and fourth columns include all other variables. As expected, the underlying temperature T_m alone explains 90% of the monthly average price variance for CDDs in summer, and 95% for HDDs in winter. The sign of the coefficients is also as expected: an increase in temperature results in a decline in the price of HDDs and an increase in the price of CDDs. Mean temperature anomalies and temperature variability are both relevant, while historical variability $\sigma(TA)$ is significant during the winter, but has no effect in summer. The coefficients for TAV are comparable across both seasons, which is intuitive when considering the effect of volatility on the option price of the underlying asset. Higher deviations in temperature variability from the historical mean increase the likelihood of experiencing extreme temperatures, thereby raising the probability of exercising the option. This, in turn, increases the value of the weather derivative contract. This finding suggests that two cities with similar average temperature anomalies may face different weather derivative prices if one city has higher temperature variability. The result supports prior literature findings that temperature volatility is greater during these months.[44] TA has coefficients with signs in the opposite direction to T_m, suggesting that traders anticipate temperatures to revert to their historical levels when a city experiences higher temperature deviations.

Thus, this analysis confirms another demand channel, where temperature variability influences the demand for temperature derivatives, supporting the notion that the weather derivatives market is highly affected by weather fluctuations (Diebold and Rudebusch (2022)).

C.4 Attention on concentrated firms

We check whether analyst attention remains significant after using firms with a greater concentration of their operations in the US. The results are indeed stronger than the results in the table in the main text.

C.5 Precipitation anomalies

Climate change can drive other weather extremes beyond temperature variability, such as precipitation extremes Allan and Soden (2008). Accordging to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), there is interconnectedness between temperature and precipitation extremes. This suggests that our estimates may capture the combined effects of both variables. To address this potential omitted variable bias, we calculate total precipitation anomalies at the state and period level using reanalysis data (ERA-5) from the European Centre for Medium-Range Weather Forecasts, spanning from

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

Table 25: Drivers of weather derivates prices

	CDD		HDD	
	(1)	(2)	(3)	(4)
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

This table presents the prices of weather derivatives regressed on temperature. Cooling Degree Days (CDD) and Heating Degree Days (HDD) are the prices of derivatives contracts are used to price the demand for energy required to cool or heat buildings, respectively. CDD represents the cumulative temperature above a baseline of 65°F, indicating cooling needs, while HDD represents the cumulative temperature below 65°F, indicating heating needs. Sample period is 2015-2020. The dependent variables are 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 monthly temperature. (2) considers all the regressors including TAV and TA .Estimation is run trough a PanelOLS employing fixed effect for cities and time. Standard errors, presented in parenthesis, are clustered both at city and time levels. Statistical significance is calculated at the 1%, 5%, and 10% levels and are indicated by ***, **, *, respectively.

1970 to 2019. Similar to our construction of our temperature metrics, we calculate the historical average total precipitation for each state and month between 1970 and 2004. Then, we subtract these averages from the realized total monthly precipitation experienced in each state from 2005 to 2019, thereby deriving precipitation anomalies on a monthly basis.

Using these anomalies, we rerun our main empirical tests by conducting 2 by 4 portfolio sorts and including the plausibly exogenous variable as an additional control for our panel regressions. For the cross-sectional portfolio sorts, we initially rank states based on their exposure to precipitation, using the median as the threshold. Within these high and low precipitation categories, we further sort the states according to either TA or TAV. Tables

Table 26: The impact of TA and TAV on the attention paid by earnings call participants to physical risk: geographically concentrated firms

	(1)	(2)	(3)	(4)
TAV	3.913**	5.467**	3.147**	4.680**
	(2.411)	(2.525)	(2.049)	(2.518)
TA	-1.262	-0.332	-1.306	-0.757
	(-0.829)	(-0.316)	(-0.829)	(-0.635)
WSJ Innov		1.620*		0.339
		(1.924)		(0.257)
SVI Innov			0.163**	0.144
			(2.163)	(1.443)
Firm FE	Yes	Yes	Yes	Yes
R Squared	0.094	0.082	0.099	0.086
Obs	11478	9458	10944	8924

This table presents results associating the physical climate exposure attention index developed by Sautner et al. (2023) to TA and TAV. The yearly innovations in the attention index are regressed onto TA and TAV with varying fixed effects. We select firms that mention their headquartered state at least 14.1% of the time relative to all states in their 10-K filings and those with more than 80% of revenues from wihtin the US. The sample period is from 2005 to 2019. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

27 and 28 show the results of the double sort strategy for TA and TAV respectively. Overall, we find that firms in regions with lower temperature variability continue to outperform their competitors in areas with higher temperature variability, regardless of whether they experience low or high precipitation. Interestingly, a pattern emerges where the outperformance is more pronounced under low precipitation conditions. This could be because high precipitation may lead to cooler conditions. In contrast, we once again find no consistent or significant relationships when we apply TA for our sorting strategy.

Next, we incorporate precipitation anomalies into our panel regressions to test whether precipitation affects our estimates on the relationship between temperature and profitability. Table 29 shows the results with this additional variable, indicating that our estimates are not subsumed.

Lastly, Table 30 presents the re-estimated relationship between temperature, precipitation, and attention paid by earnings call participants. We find a positive relationship between precipitation and attention paid to physical risks; however, this does not change our primary coefficients attached to TAV.

Table 27: Abnormal returns to portfolios sorted on precipitation and TA

Panel A: Portfolios sorted on low precipitation and TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.747**	0.059	0.043	-0.002
	(0.029)	(0.545)	(0.670)	(0.988)
Portfolios 2,3,4	0.717**	0.041	0.008	0.013
	(0.042)	(0.687)	(0.928)	(0.881)
Portfolio 5	0.810**	0.124	0.103	0.059
	(0.011)	(0.435)	(0.527)	(0.732)
Portfolio 1 - 5	-0.063	-0.066	-0.060	-0.060
	(0.771)	(0.752)	(0.777)	(0.791)
	(0.528)	(0.362)	(0.529)	(0.557)

Panel B: Portfolios sorted on high precipitation and TA

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.716*	0.017	0.015	0.046
	(0.052)	(0.892)	(0.908)	(0.738)
Portfolios 2,3	0.735**	0.074	0.050	0.115
	(0.031)	(0.451)	(0.635)	(0.240)
Portfolio 4	0.673**	0.026	0.015	0.019
	(0.024)	(0.822)	(0.901)	(0.886)
Portfolio 1 - 4	0.043	-0.009	-0.000	0.028
	(0.812)	(0.959)	(0.998)	(0.888)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to precipitation anomalies and the mean of temperature anomalies (TA). Each month t, we sort U.S. states into two groups (median) based on their realization of precipitation anomalies, then, we further sort these groups into four (quartiles) based on their realization of TA. The returns of the firms headquartered in these grouped states are then value-weighted to generate portfolio returns, which are rebalanced monthly. Panel A includes firms experiencing lower-than-normal precipitation, while Panel B encompasses those with higher-than-normal precipitation. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (colder states) and portfolio 4 includes those firms in states experiencing the highest values of TA (warmer states). We group the middle two portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors. "Portfolio 1–4" reports the return spread between portfolios 1 and 4, i.e., the return difference between the least and most exposed portfolios. To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated in the U.S. The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 28: Abnormal returns to portfolios sorted on precipitation and TAV

Panel A: Portfolios sorted on low precipitation and TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	1.044***	0.378***	0.313***	0.313**
	(0.001)	(0.006)	(0.009)	(0.020)
Portfolios 2,3	0.703**	0.057	0.027	0.010
	(0.025)	(0.402)	(0.719)	(0.889)
Portfolio 4	0.508	-0.245	-0.273*	-0.251*
	(0.212)	(0.123)	(0.077)	(0.099)
Portfolio 1 - 4	0.536***	0.622***	0.586***	0.564***
	(0.007)	(0.002)	(0.002)	(0.003)

Panel B: Portfolios sorted on high precipitation and TAV

	Excess Return	FF3-Factor	FF3+Mom+Liq	FF5-Factor
Portfolio 1	0.966***	0.293**	0.352**	0.260**
	(0.001)	(0.017)	(0.014)	(0.030)
Portfolios 2,3	0.680*	0.019	-0.016	0.022
	(0.055)	(0.808)	(0.835)	(0.796)
Portfolio 4	0.627*	-0.094	-0.085	-0.030
	(0.067)	(0.422)	(0.469)	(0.794)
Portfolio 1 - 4	0.340**	0.387**	0.438**	0.290*
	(0.018)	(0.012)	(0.011)	(0.063)

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to precipitation anomalies and the standard deviation of temperature anomalies (TAV). Each month t, we sort U.S. states into two groups (median) based on their realization of precipitation anomalies, then, we further sort these groups into four (quartiles) based on their realization of TAV. Panel A includes firms experiencing lower-than-normal precipitation, while Panel B encompasses those with higher-than-normal precipitation. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TAV (low variability) and portfolio 4 includes those firms in states experiencing the highest values of TAV (high variability). We group the middle two portfolios together by equal-weighting their respective returns and denote them as "Portfolios 2,3". We report the alphas of each portfolio after controlling for the Fama-French 3 factors, Carhart 4 factor and liquidity factor, and the Fama-French 5 factors. "Portfolio 1–4" reports the return spread between portfolios 1 and 4, i.e., the return difference between the least and most exposed portfolios. To control for operational dispersion, we select firms that mention their headquartered state at least 8.2% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 65% of their revenues generated in the U.S. The sample period is from March 2005 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and are calculated using the Newey-West correction for 6 lags.

Table 29: Temperature, precipitation exposure and firm profitability

	(1) All	(2) BusEq	(3) Chems	(4) Cnstr	(5) Durbl	(6) Enrgy	(7) Hlth	(8) Manuf	(9) Money	(10) NoDur	(11) Other	(12) Shops	(13) Telcm	(14) Trans	(15) Utils
TAV	-1.08***	-2.14***	-1.39	-2.38**	-2.47**	2.21**	-2.11**	-0.87*	-0.37*	-0.88	-1.51	-0.79	-0.11	-1.36**	0.68*
	(-3.38)	(-3.98)	(-1.14)	(-2.68)	(-2.13)	(2.65)	(-2.65)	(-1.97)	(-1.69)	(-1.08)	(-1.45)	(-1.47)	(-0.09)	(-2.17)	(1.81)
TA	0.05	-0.08	-0.15	0.26	0.32	-0.04	0.46	0.04	0.05	0.29	-0.21	-0.16	0.36	0.36*	-0.53***
	(0.50)	(-0.54)	(-0.56)	(1.00)	(1.45)	(-0.09)	(0.80)	(0.21)	(0.80)	(1.20)	(-0.65)	(-0.60)	(0.78)	(1.98)	(-3.38)
Precipitation	0.08	-0.05	-0.49	0.00	-1.48*	0.51**	0.43**	0.15	0.11	0.06	0.19	-0.12	0.04	-0.37	0.14
	(1.38)	(-0.16)	(-0.96)	(0.04)	(-1.85)	(2.82)	(2.10)	(0.59)	(0.77)	(0.15)	(0.91)	(-0.37)	(0.07)	(-1.62)	(1.44)
L.Leverage	-5.30	-6.82	27.07	9.21	-29.90	31.32	-18.03	13.16	-4.47	-4.97	-28.10***	14.96	-45.19**	1.41	90.02***
	(-1.00)	(-0.88)	(0.52)	(0.62)	(-0.93)	(0.76)	(-1.29)	(0.71)	(-0.77)	(-0.30)	(-3.27)	(0.76)	(-2.90)	(0.08)	(6.86)
L.Invest Rt	-1.03	-6.43**	-6.59***	-4.75	9.63	0.60	-0.79	-3.84	-1.75	-5.57	-1.01	-2.82	0.18	0.32	-0.71
	(-1.21)	(-2.29)	(-3.30)	(-0.80)	(1.72)	(0.48)	(-0.29)	(-1.39)	(-1.43)	(-0.67)	(-0.62)	(-1.19)	(0.24)	(0.33)	(-1.23)
L.Bk to Mkt	-12.67***	-19.17***	-17.88***	-16.78***	-9.00*	-20.31***	-8.94**	-22.43***	-3.86**	-3.95	-17.38***	-9.75***	-17.48***	-10.75**	-0.62
	(-10.53)	(-3.84)	(-3.68)	(-4.26)	(-1.84)	(-4.10)	(-2.45)	(-6.12)	(-2.21)	(-0.68)	(-2.82)	(-3.86)	(-3.39)	(-2.72)	(-0.48)
L.Earn/Shr	-2.09***	0.53	-1.48	3.22*	3.86*	-2.68***	-8.81***	0.05	-0.17	-2.74	-0.38	-1.37	-2.02	-0.88	-0.99
	(-4.57)	(0.30)	(-0.75)	(1.99)	(1.84)	(-4.47)	(-5.94)	(0.06)	(-0.46)	(-1.46)	(-0.28)	(-1.66)	(-0.90)	(-0.80)	(-1.66)
L.Tobins Q	-3.84***	-4.28**	-4.74*	-0.18	-0.74	0.27	-5.02***	-4.65**	2.93	0.86	-4.46*	1.94	-6.55*	-4.76*	15.10***
	(-9.07)	(-2.59)	(-1.91)	(-0.11)	(-0.26)	(0.06)	(-8.97)	(-2.46)	(1.13)	(0.55)	(-1.96)	(1.61)	(-1.81)	(-1.93)	(2.96)
L.ROA	0.01	-0.07	0.01	-0.21**	-0.18	0.15*	0.11***	-0.02	-0.09**	-0.08*	-0.09	-0.06	-0.10	-0.03	-0.14***
	(0.40)	(-1.29)	(0.08)	(-2.62)	(-1.30)	(2.19)	(5.30)	(-0.76)	(-2.32)	(-1.88)	(-1.23)	(-1.05)	(-0.91)	(-0.32)	(-3.77)
L.PPE/Assets	-16.83	-38.29	-25.66	-14.53	-72.00	26.72	-64.31	28.19	3.03	14.42	37.91*	-34.43	25.35	-22.85	-50.75***
	(-1.15)	(-1.48)	(-0.48)	(-0.37)	(-1.03)	(1.08)	(-0.89)	(1.03)	(0.12)	(0.88)	(1.84)	(-1.60)	(1.45)	(-1.25)	(-4.62)
Constant	8.46**	1.99	1.32	0.91	26.61	-21.23	-9.14	-5.33	1.91	12.50	2.16	8.25	13.61	27.37***	-6.48
	(2.43)	(0.41)	(0.09)	(0.08)	(1.35)	(-1.66)	(-1.04)	(-0.64)	(0.82)	(1.69)	(0.60)	(1.27)	(1.60)	(3.23)	(-0.80)
IndYear FE	Yes	No	No	No	No	No	No	No	No	No	No	No	No	No	No
FirmYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Squared	0.73	0.68	0.75	0.46	0.73	0.41	0.80	0.56	0.64	0.49	0.52	0.52	0.46	0.64	0.24
Observations	60952	8071	1385	2729	1411	1335	6506	6103	14358	3669	4011	4354	1274	2593	3153

This table presents the results of regressing quarterly income, scaled by total assets from the prior quarter, to the quarterly mean of temperature anomalies (TA), the standard deviation of temperature anomalies (TAV), and precipitation anomalies (Precipitation). The control variables include leverage, capital investment rate, log book-to-market equity, Tobin's Q, return on assets, earnings per share, capital expenditure, and plant, property, and equipment over total assets, all from the previous quarter. To control for operational dispersion, we select firms that mention their headquartered state 8.2% of the time (10th percentile) over all other states in their 10K filings and firms with more than 65% of revenues in the US. The quarterly sample period is from 2005 to 2019. All specifications include firm by year fixed effects. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

Table 30: The impact of TA and TAV on the attention paid by earnings call participants to physical risk

	(1)	(2)	(3)	(4)
TAV	4.278***	5.440***	3.643**	4.794**
	(2.738)	(2.758)	(2.321)	(2.580)
TA	-0.651	0.429	-0.629	0.091
	(-0.616)	(0.548)	(-0.586)	(0.096)
Precipitaion	0.094	0.247	0.074	0.166
	(0.324)	(0.714)	(0.209)	(0.390)
WSJ Innov		1.686*		0.609
		(1.962)		(0.466)
SVI Innov			0.150**	0.123
			(2.409)	(1.422)
Firm FE	Yes	Yes	Yes	Yes
R Squared	0.076	0.063	0.081	0.068
Obs	15779	13065	15023	12309

This table presents results associating the physical climate exposure attention index developed by Sautner et al. (2023) to the mean of temperature anomalies (TA) and the standard deviation of temperature anomalies (TAV). We also include precipitation anomalies at the state level (Precipitation). The yearly innovations in the attention index is regressed onto TA and TAV with varying fixed effects. We control for national and state-specific attention towards climate change. *WSJ Innov* represents the innovations in the national Wall Street Journal news index developed by Engle et al. (2020). *SVI Innov* represents innovations in the Google Search topic "Climate Change" at the state level. We select firms that mention their headquartered state 8.2% of the time over all other states in their 10Ks and those with more than 65% of revenues from the US. The sample period is from 2005 to 2019. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.