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

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Abstract

Firms exposed to abnormal temperature variability underperform. A long-short strategy exploiting cross-sectional spatial variation in this metric earns a market-adjusted alpha of 4.9% annually. The effect operates through lower firm revenue and profitability, with heterogeneous effects across industries. Temperature variability propagates through behavioral updating and attention channels, and reduces both consumer spending and worker productivity. Firms more exposed to this variability exhibit higher idiosyncratic return volatility and greater dispersion in analyst forecasts, reflecting uncertainty in pricing damages from extreme temperatures and its swings.

Keywords: Temperature variability, Stock Returns, Firm Performance.

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Intensifying extreme temperatures, exacerbated by climate change, are affecting firms through both production (Pankratz and Schiller, 2024) and demand-side disruptions (Lee and Zheng, 2024). Yet, the effects of abnormal or anomalous temperatures on asset prices and firm performance vary across studies, with some finding no contemporaneous adjustment in returns (Cuculiza et al., 2024), negative premia (Pankratz et al., 2023), positive premia (Acharya et al., 2022), and others finding null effects (Addoum et al., 2020).[1] Each study uses varying methodological approaches to constructing exposure measures, further complicating cross-study comparisons and consensus building. How can this seemingly contradictory evidence be reconciled with asset pricing theory that predicts firms exposed to realized climate shocks should underperform their peers (Pástor et al., 2021)?

This paper revisits the debate by proposing a metric that represents abnormal shifts in temperature variability driven by climate change. This approach captures not only the rising frequency and intensity of temperature swings (Kotz et al., 2021; Wu et al., 2025), but the incidence of extremes in comparison to other measures (Katz and Brown, 1992). Our key contribution is that firms with greater realized exposure to changes in the standard deviation of temperature anomalies, relative to a rolling historical baseline, systematically earn lower returns in the cross-section from 1993 to 2019. The mechanisms underlying this return response operate through multiple channels such as suppressed consumer demand and reduced labor productivity in temperature-sensitive industries that diminish firm revenues and profitability. Market participants also update their beliefs about the damaging effects of climate change during these volatile periods, resulting in heightened uncertainty about the economic performance of firms. This uncertainty is reflected as greater idiosyncratic volatility and increased dispersion in analyst earnings forecasts for affected firms.

Our identification strategy isolates firms' spatial exposure to abnormal temperature volatility. We construct this exposure using surface temperature data from National Oceanic and Atmospheric Administration, aggregated to the U.S. state level. Our approach defines a

[1] We use the terms "abnormal" and "anomalous" temperatures interchangeably.

baseline for abnormal temperature variability using a 25-year rolling window, long enough to anchor expectations and to capture evolving climate normals—mirroring how agents update beliefs based on historical experience (Deryugina, 2013). This setting allows us to test the effects of arguably exogenous temperature shocks (Auffhammer et al., 2013; Dell et al., 2014) on firms over time and space. The Compustat and CRSP universe of firms are matched to their headquartered states, under the assumption that operations are concentrated nearby. 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 to examine the impact of state-level exposure to abnormal temperature variability on returns from 1993 to 2019. A monthly strategy that longs firms in the least affected states and shorts those in the most affected states generates a factor-adjusted return of 4.9% annually, reflecting the outperformance of firms located in regions with lower temperature variability. Double sorts on temperature variability and then size yield a return of 6.05% for small firms and 3.87% for larger ones, suggesting a stronger effect on smaller firms. Abnormal returns persist after controlling for 189 other monthly anomalies using multiple hypothesis testing (Chen and Zimmermann, 2021). Fama and MacBeth (1973) regressions show that the negative relation between temperature variability and returns holds after controlling for firm characteristics and alternative climate exposures, including average temperature changes, precipitation, and wildfire risk.[2] This finding highlights a key contribution: equities are responsive to shifts in abnormal temperature variability.

[2]We recognize that climate change is amplifying other weather phenomena beyond temperature variability, such as precipitation extremes and wildfires, however, there is theoretical and empirical support for focusing on temperature variability. Temperature changes are linked with other weather phenomena. 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).

Does the return reaction stem from operational disruption, shifts in attention and beliefs, or from increased uncertainty about climate damages? The existing literature on investor attentiveness to climate shocks is ambiguous. 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.[3] We disentangle these three channels and find evidence consistent with each mechanism.

First, to assess the effects on firms' operating performance, we analyze how abnormal temperature variability influences revenues and profitability. We find that revenues fall more sharply than profits—an average firm loses $5.4 million in revenues and $1.65 million in profits over a quarter. The drop in revenues points to reduced demand or operational disruptions, while the smaller decline in profits suggests that firms offset some of the revenue loss by cutting costs, consistent with cautious managers following an uncertainty shock (Bloom, 2009). The effects vary across sectors with the business equipment, construction, manufacturing, durables, finance, and retail shopping facing negative responses to variability. Conversely, the utilities and energy industries see increased revenues with higher variability.

The primary driver behind these patterns is reduced consumption and labor productivity in response to extreme temperatures (Starr, 2000; Graff Zivin and Neidell, 2014; Neidell et al., 2021) and the swings between hot and cold extremes. Using household expenditure data from the US Consumer Expenditure Survey, we find that a one-standard-deviation increase in variability reduces household spending by $199 per year or $64 million per year when extrapolated to the 540,000 households interviewed. Substantiating our profitability results, we observe a similar heterogeneous impact on expenditure: spending on non-durables, durables, and apparel decreases with variability, while utility spending increases.

Abnormal temperature variability also weighs on labor productivity. Data from the American Time Use Survey show that individuals in temperature-sensitive industries work three fewer minutes per week when exposed to greater temperature variability. This result

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

aligns with Neidell et al. (2021), who document a 2.6 minute reduction in work time for high-risk industry workers on days reaching 90°F.

Second, to investigate whether abnormal temperature variability affects beliefs, we collect survey data from the Yale Program on Climate Change Communication. In the survey, 65% of respondents report believing in climate change; however, only 33% report personally experiencing its harmful effects. This wedge is surprising given the evidence that extreme weather events have intensified since 1950 (Stocker et al., 2013), implying that even in the presence of increasing exposure, agents fail to integrate risks into their subjective perceptions. We find that temperature variability increases the share of people who report they have been exposed or harmed by climate change, acting as a salient "wake-up call" to its damages. Public and investor attention also respond as the number of climate-related news articles in the Wall Street Journal rises (Engle et al., 2020), and both Google searches and earnings-call discussions related to the climate rise with these shocks (Sautner et al., 2023).

Third, we test if temperature variability generates uncertainty for investors. Fama-MacBeth regressions show that the measure is positively related to realized idiosyncratic return volatility. Analysts' earnings forecasts for exposed firms also become more dispersed, and earnings surprises turn modestly negative, indicating that analysts struggle to estimate the true impact. Shifts in investor and media attention further support this mechanism, as market participants seek information to assess damages. The evidence therefore points to "impact uncertainty" in the spirit of Kruttli et al. (2025), reflecting ambiguity over how extreme temperatures and their swings affect firm operations. While heterogeneous beliefs may also contribute to price dispersion Baldauf et al. (2020), the localized nature of temperature variability and firm cost-cutting are more consistent with increased impact uncertainty.

This study advances the financial literature on climate change by: (i) developing a novel metric of temperature exposure that has real financial impacts on firms and investors, and (ii) identifying the channels through which these effects are manifested. Related studies (Addoum et al., 2020; Pankratz et al., 2023; Acharya et al., 2022; Pankratz and Schiller, 2024)

examine the effects of temperature on financial markets based on predetermined thresholds or the right tail of the distribution. In contrast, our statistic focuses on variability and is grounded in the updating of climate expectations over a rolling window—using a period long enough to capture scientific climate normals, but short enough to match the horizon over that individuals can recall weather patterns (Deryugina, 2013; Akerlof et al., 2013). This approach allows us to measure abnormal climate-induced temperature extremes.

Our emphasis on returns and uncertainty distinguishes this work from Addoum et al. (2023) and Pankratz et al. (2023). Their studies use absolute temperatures to show seasonal, industry-specific effects on profitability, but find no contemporaneous impact on equity prices and limited investor response.[4] 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. Additionally, survey evidence points to "unexpectedness" of weather phenomenon anchored on agents historical experiences (Moore et al., 2019). Our rolling window approach captures how markets respond to extreme deviations from recent norms, effectively triggering the attention and belief-updating process.

Many studies rely on climate 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. Schlenker and Taylor (2021) demonstrate that participants in weather markets revise their expectations by incorporating warming trends. We show that abnormal temperature variability elicits stronger belief and attention responses—and, in turn, return reactions—than shocks to mean abnormal temperatures, precipitation, or wildfire risk.

Cuculiza et al. (2024) argue that markets do not immediately price temperature changes, showing that firms sensitive to average temperature anomalies earn lower future returns. Their results point to persistent mispricing of gradual climate risks, resolved over longer

[4]Both also benchmark exposure against a fixed historical mean or a threshold, such as days above 30°C.

horizons. By contrast, we find that the market responds contemporaneously to abnormal temperature variability, with uncertainty resolving quickly. We find no contemporaneous return response when using average temperature deviations, highlighting a difference between transitory reactions to variability and slower moving average changes.

1 Temperature anomalies, variability, & learning

Climate scientists describe deviations in temperature as anomalies, a departure in temperature from a longer historical normal. Differencing the temperature variable by location is econometrically useful as it removes time-invariant, location-specific baseline climate conditions that could otherwise confound the estimation of temperature-related effects (Dell et al., 2012). What remains is the short term, exogenous, weather variation that is influenced by climate change. An additional empirical advantage is that these anomalies, when sufficiently aggregated across time, approach near-normality.

It is possible to construct anomalies to mirror a behavioral learning framework, in which economic agents revise their beliefs in response to relevant, observable phenomena (Alevy et al., 2007). The financial literature has applied this framework to temperature, with Choi et al. (2020) using a rolling 10-year period to measure abnormal temperature, and Pankratz and Schiller (2024) using the onset of a supply-chain relationship as a starting point for a reference period. Typically, these constructions assume that agents form a posterior belief about the *mean* of the probability distribution of a temperature metric—for example, the average temperature or number of days above 30°C over a historical period.

Averaging across time periods is useful to abstract from short-run variability to represent climate normals. The National Oceanic and Atmospheric Administration (NOAA) and the World Meteorological Organization, recommend calculating normals over 30-year periods to smooth out interannual variability, cyclical phenomena such as El Niño, and decadal oscillations to capture the underlying climate signal. This scientific climate consensus, however,

contrasts with the heterogeneity in empirical approaches regarding the appropriate observation period for modeling agents' posterior probability distributions in Bayesian learning frameworks. For instance, Deryugina (2013) use a 60-year static historical period, while Choi et al. (2020) uses a shorter 10-year rolling window. Direct survey level evidence from Akerlof et al. (2013) suggests that agents are able to accurately recall a difference in current seasonal weather patters from the most recent 20-year period.[5]

To balance scientific rigor with behavioral observations, we first define day-to-day temperature anomalies for a given location as deviations in the observed daily maximum temperature from a historical rolling average of 25-years:

$$\text{TA}_{s,[d,m,y]} = T_{s,[d,m,y]} - \overline{T}^{[y-25,\,y-1]}_{s,[d,m,y]} \tag{1}$$

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 $\overline{T}_{s,[d,m]}$ denotes the historical average maximum temperature at the same location s and on the same day d and month m, over the previous 25-years.[6] This historical average is calculated using a window of 3 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 prior and following days.

For a location-specific, monthly measure of day-to-day temperature anomaly, we average the daily anomalies over the course of a given month:

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

[5]It is important to clarify that the historical reference period should not be conflated with the time required for agents to update their beliefs. Deryugina (2013), for example, show that 30-day periods of abnormal weather lead to revision. Moreover, the more extreme the anomaly, the stronger the shift in beliefs.

[6]$\overline{T}_{s,[d,m]}$ is not a constant, varying across location s and time, thus affecting both the time-series and cross-sectional properties of $TA_{s,[d,m,y]}$.

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

Prior literature adopts a similar methodology to TA, differencing current average temperatures from historical averages. Numerous studies (Dell et al. (2014) and Burke et al. (2015)) use temperature anomalies and find effects across a wide array of observable macroeconomic and other outcomes, including productivity, production output, economic growth, migration, and mortality (Dell et al. (2014) and Carleton and Hsiang (2016)).[7] In the climate finance literature, Choi et al. (2020), Cuculiza et al. (2024), and Kelly et al. (2005) use this approach to produce a normally distributed measure for their empirical analysis. In contrast, Pankratz et al. (2023) and Addoum et al. (2020) focus on abnormal heat extremes, measuring the difference in the number of days exceeding 30°C within a period. This results in a zero-inflated distribution, reflecting the many months without any heat days. Each approach reflects a methodological choice based on distributional properties and theoretical assumptions about economic impact.

Our goal is to construct a general measure which represents both temperature extremes and the more frequent and intense swings in temperatures occurring (Kotz et al., 2021). We therefore use anomalies in variability rather than anomalies in mean for two reasons: (1) temperature extremes are more sensitive to changes in the variability of temperature anomalies than to changes in their mean (Katz and Brown, 1992; Schar et al., 2004) and (2) the second moment abstracts from predetermined thresholds or right-tail distribution constraints, capturing both abnormally cold and hot temperatures, each known to produce

[7]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)).

economically damaging outcomes.

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 a rolling historical average intra-month variability of temperature anomalies, calculated over a prior 25-year period.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 temperature anomalies deviate from their average value for that month.

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

$$TAV_{s,[m,y]} = \sigma(TA_{s,[m,y]}) - \overline{\sigma}(TA_{s,[m]})^{[y-25,\, y-1]}. \tag{4}$$

TAV quantifies the deviation of 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 temperature anomalies are more dispersed than usual, suggesting that location s is experiencing more frequent and intense swings in temperature. In Section A.1.1 of the Internet Appendix, we outline the dynamics of abnormal temperature variability and compare its characteristics to TA.

Our approach to constructing temperature variability differs from Donadelli et al. (2019). They compute yearly volatility from temperature levels, while we first calculate temperature anomalies. Their use of the pre-industrial period (1659–1759) as a reference reflects a climate science perspective, whereas we base priors on recent decades, aligning with a

Bayesian updating framework. They also treat anomalies in both distribution tails as equally damaging by applying the absolute value operator. Finally, our reference volatility accounts for regional variation, avoiding aggregation bias from national-level data (Auffhammer et al., 2013), reflecting how economic agents form expectations and respond to shocks.

2 Data

2.1 Data sources

Our sample is constructed by merging data from several databases covering financial, economic, survey, and climate data. Table 1 provides summary statistics for all variables used and Table 18 in the Appendix describes them.

2.2 Temperature

We use the nClimGrid-Daily product from the National Oceanic and Atmospheric Administration, which provides daily gridded fields and area averages of maximum temperatures for the contiguous United States from 1951 to 2019. The nClimGrid data are organized on a grid with a resolution of 1/24 of a degree, or roughly 4 by 4 kilometers. We choose nClimGrid over other products, such as Berkeley Earth, because it offers finer resolution, is focused on the United States, and provides raw temperature values.

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 consider state-level 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

For financial data, we turn to the Center for Research in Security Prices (CRSP) files to gather stock returns and the Standard and Poor's Compustat database for financial information. We source daily and monthly stock returns for all listed US companies from 1993 to 2019 and adjust for delisting. Financial variables are obtained from Compustat. Table 1 presents summary statistics of various financial parameters, including log book-to-market ratio, return on assets, leverage, Tobin's Q, and plant, property and equipment over total assets. Return and financial ratios are winsorized at 1%.

We obtain data on the attention paid by earnings call participants to climate change exposure from Sautner et al. (2023). Analyst data from the Institutional Brokers Estimate System (I/B/E/S) are also extract.

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 these firms and identify the number of times a U.S. state is mentioned in sections 1A, 2, 6, and 7. The firm-headquarter count is calculated by dividing the total number of mentions of the headquartered state by the total mentions of all states from 1993 to 2019. 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 1 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 (5%) which leaves 10,614 firms remaining in the sample for the contiguous 48 states.

Sales and operations of many US-based firms 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 1993–2019 to represent the firm's sales concentration over this period. Figure 2 shows the left-skewed distribution of US revenue concentration for the firms in the sample. We retain only those companies with more than 73.5% of their revenues originating from within the US, leaving 9,529 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. 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 Other data

We obtain precipitation and wildfire risk data from the Gridded Surface Meteorological (gridMET) dataset. We average precipitation and the burning index—which describes the potential effort required to contain a fire—across each of the contiguous states. We then calculate

deviations of each variable from its average in a manner similar to TA, as outlined in Section 1. Since these data are only available from 1979, we use a 13-year rolling average.

Economic data, including the state-level all-transactions house price index, population, total personal income, unemployment rate, and the U.S. consumer price index, are obtained from the Federal Reserve Bank of St. Louis. We collect household survey expenditure data from the Bureau of Labor Statistics and time worked from the American Time Use Survey.

Finally, we collect survey data on climate beliefs from the Yale Program on Climate Change Communication, attention to climate change from Google search volumes, and the Wall Street Journal index from Engle et al. (2020).

3 Returns and firm performance

Our analysis begins with a set of cross-sectional return exercises. By constructing a zero-cost trading strategy for anomalous temperature variability, we compare the realized returns of firms most affected and least affected by temperature changes. These aggregate return patterns are then confirmed with a set of Fama-Macbeth regressions.

An aggregate return response may be attributable to changes in temperature variability that impact firm value and business profitability. Therefore, we next 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.

3.1 Empirical strategy

We hypothesize that temperature impacts firm performance and assert that our statistical representation of anomalous variability meaningfully captures these effects. To empirically evaluate our hypothesis, we exploit medium to 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 6, this further reduces measurement bias as firms may operate across neighboring states. Additionally, we exclude firms with significant international revenue shares.

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.

We address relocation concerns by sorting states into quartiles and quintiles based on their monthly TAV exposure. Table 2 reports transition matrices where each entry gives the percent of times a state moves from one percentile tier at month t to another at $t+1$. The left column lists the starting percentile and the other columns show the percentile at $t+1$.

The matrices indicate that states' TAV exposures about equally likely to rise or fall in the exposure distribution, suggesting similar temperature variability risks across regions.[8]

Controlling for firm investment in climate resilience poses a challenge due to unobservable managerial decisions. Research by Pankratz and Schiller (2024) suggest that adaptation efforts, such as terminating supply chain contracts, typically unfold 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 include firm-by-year fixed effects, which help to minimize the influence of adaptation on our estimates. Additionally, our 25-year rolling window construction of temperature volatility partially mitigates concerns of long-term trends in technological adaptation compared to a static historical baseline.

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 and a fire danger metric derived from the US National Fire Danger Rating System as controls.

3.2 Cross sectional returns

We begin by examining whether the returns of exposed firms respond to the effects of temperature as statistically represented by our measure of anomalous temperature variability. The literature on a temperature premia is mixed (Gostlow, 2024), with some finding a positive premia (Acharya et al., 2022; Donadelli et al., 2019) and others finding no contemporaneous return reaction (Pankratz et al., 2023; Addoum et al., 2020). We hypothesize that anomalous temperature volatility serves as a proxy for both the negative consequences of extreme weather and periods of heightened uncertainty. When these conditions are realized, they manifest as negative shocks for affected firms. Thus, we expect to observe a negative con-

[8] 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.

temporaneous association between anomalous temperature volatility and firm returns. This is consistent with the interpretation of Pástor et al. (2022), who show that realized shocks to climate concerns have immediate adverse impacts on firms most exposed to such risks.

We construct zero-cost trading strategies by sorting states into percentile groups based on monthly realizations of TAV experienced by 48 US states between January 1993 and December 2019.[9,] Firm returns are then allocated to these groups based on whether their operational footprint is within those states, forming either four or five value-weighted portfolios that are rebalanced monthly.[10] The lowest percentile portfolio contains firms experiencing lower values of TAV, while the highest percentile portfolio includes firms faced with greater values of the standard deviation of the distribution of temperature anomalies. Finally, we calculate long-short (L/S) returns by subtracting the returns of firms in the lowest percentile from those in the highest.

Figure 3 plots the L/S abnormal returns for TAV when applying quartile and quintile sorts, illustrating portfolios sorted by TAV generates positive abnormal returns. Therefore, on average, firms located in states experiencing minimal changes in the standard deviation of temperature anomalies outperform those in states with greater changes.

The first columns of Panels A (quartile sort) and B (quintile sort) in Table 3 present excess returns for each strategy after adjusting for the market portfolio. The first and third rows in each panel show monthly realized abnormal returns for long and short strategies and the middle portfolios are averaged and presented in the second. The final rows of each panel display L/S portfolio returns, revealing that each strategy generates positive average monthly excess returns between 0.38 and 0.4 basis points per month. The annualized Sharpe ratio of the market adjusted strategy is 0.56, comparable to the Sharpe ratios of the aggregate equity premium.

Next, we investigate the extent to which other risk factors explain the return pattern of

[9]As discussed in Section 2.4, we remove Alaska and Hawaii

[10]We remove firms that only mention their headquartered state 3.44% of the time (the 10th percentile) over all other states in their 10-K filings.

the temperature-sorted L/S portfolios. The remaining columns report the alphas augmenting for these common risk factors, including the Fama-French three-factor model (second column), Pástor and Stambaugh's liquidity factor (third column), Frazzini and Pedersen's (Frazzini and Pedersen, 2014) betting against beta (fourth column), the Fama-French five-factor model (fifth column) saturated with Carhart's momentum factor. We find that the cross-sectional return spread across portfolios sorted on TAV is not subsumed by these risk factors, and the alphas in the L/S portfolio remain statistically significant. The results imply that firms operating in states with greater abnormal variability in temperature consistently underperform those in less variable temperature environments, suggesting that investors are not indifferent to temperature variability exposure.

Prima facie, the results seem inconsistent with asset pricing theory, as the strategy's short side should have greater expected returns to compensate for risk. However, our measure captures realized abnormal volatility shocks by differencing from the historical climate expectation. Our interpretation aligns with Pástor et al. (2021)——the asset values of exposed firms decrease when climate conditions unexpectedly worsen. This reduction in asset prices can occur in two ways which we explore in the following sections: (1) a reduction in cash flows through business operations, and (2) a reallocation of capital away from exposed firms due to investor preferences.

We conduct a variety of robustness tests to confirm this main result. To address concerns of spatial correlation and to validate that the relationship is not spurious, we conduct placebo tests in section A.1.1. For the placebo tests, we preserve the structure of TAV by randomly shuffling the monthly values of TAV in the cross-section and conducting quartile and quintile portfolio sorts 5,000 times each. After adjusting for the Fama-French 3-factor model, less than 10 iterations of the portfolio sorts produce greater abnormal returns than the original strategies. The placebo tests also ameliorate concerns that the sorting procedure captures other state-level variations that confound the relationship between temperature and returns. Nonetheless, we conduct similar portfolio sorts using deviations in average temper-

ature, precipitation, and wildfire risk in Section A.1.2 to show that temperature volatility is key driver of returns.

Next, we alleviate size-related concerns by performing a double sort on temperature volatility and firm size. First, we categorize states into terciles based on TAV, then sort each tercile into two groups using firms' previous quarter total assets as a size proxy. Panels A and B in Table 4 confirm the return pattern persists across both small and large firms, with stronger effects among smaller firms. This is logical since smaller firms tend to be more geographically concentrated, increasing their exposure to abnormal temperature conditions.

The L/S portfolio strategy cannot simultaneously control for many firm-related characteristics. Consequently, we use Fama-Macbeth regressions to estimate the risk premiums associated with abnormal temperature volatility, incorporating a broader set of controls. For firm controls, we include the log of total assets, leverage, log book-to-market equity, return on assets, Tobin's Q, and the log of plant, property, and equipment over assets. We also account for state-level characteristics such as year-over-year changes in the unemployment rate, house price index, and personal income. The first column of Table 5 uses this control set to demonstrate that abnormal temperature volatility yields a negative risk premium, consistent with the long-short portfolio results. Columns (2) through (5) progressively include risk factors and industry-level fixed effects across the 12 sectors defined by Fama and French, plus the construction and transportation sectors known for temperature sensitivity (Graff Zivin and Neidell, 2014). In the final column, we incorporate other physical risk factors and the innovations of the Wall Street Journal Climate Change News Index from Engle et al. (2020) as a proxy for unexpected market-wide investor attention to physical and transition risks related to climate change. The abnormal temperature volatility premium remains consistent across all specifications.

Finally, we assess whether the estimated abnormal return is attributable to known pricing anomalies. Using 189 monthly portfolios of predictors from Chen and Zimmermann (2021), we regress the sorted quartile and quintile L/S portfolio returns on the Fama-French

3-factor model, adding each of the 189 anomalies one at a time. Figure 4 shows histograms of the regression t-statistics, with lines indicating significance at the 5% and 10% levels. All alphas, except two, are significant at the 5% level, while the two exceptions being significant at the 10% level. These exceptions, announcement returns (Chan et al., 1996) and dividend seasonality Hartzmark and Solomon (2013), are the strongest predictors in the sample of Chen and Zimmermann (2021). Given that performing 189 regressions raises concerns about multiple testing, we adjust for the False Discovery Rate as per Benjamini and Yekutieli (2001). This adjustment results in a marginal downward shift of the critical P-value to 0.049. Overall, the consistent statistical significance of the abnormal returns suggests that realizations of abnormal temperature variability represents a novel source of systematic risk orthogonal to existing factor structures.

3.3 Efficiency and profitability

The L/S portfolio results indicate that, on average, firms operating in states with smaller deviations in temperature variability consistently outperform those in more variable 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 leverage the exogenous geographic and time-series variation of TAV to investigate whether differences in operational performance, in terms of quarterly asset efficiency (revenues scaled by total assets) and profitability (income before extraordinary items scaled by total assets), can be observed in firm-level data.

We consider the following specification:

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

where y is either revenue or income of firm i, headquartered in state s, in calendar quarter t. Income is scaled by the previous quarter's total assets to produce a measure of profitability, which is then multiplied by 100 for interpretability. TAV are the the deviations in temperature variability over the same quarter. The firm-level control variables, $D_{i,t-1}$, lagged by one quarter, include log of total assets, leverage, log book-to-market equity, Tobin's Q, return-on-assets, and log of 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-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.[11]

Table 6 details our findings on firm efficiency, starting with all firms in the sample in the first column. An increase in TAV leads to significantly worse performance, indicated by lower operational efficiency, 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. Specifically, a one standard deviation rise in TAV reduces the asset-turnover ratio by 0.087% in a single quarter. This effect is approximately double what Pankratz et al. (2023) reports, where a similar increase in hot days diminishes the ratio by 0.143% over a year for non-U.S. headquartered firms. To translate the effect into a dollar change in revenue, I multiply the change in the ratio by the average asset base ($6.1 Billion) to show that the reduction in revenues is about $5.42 million.

Before turning to the industry-specific results in the remaining columns, I analyze the

[11]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.

aggregate effects of TAV on profitability, which is net of costs. This differentiation is warranted as the ratio assimilates both revenue fluctuations and the countervailing adjustments to operating costs in response to rising temperature volatility. For example, greater uncertainty may cause firms to act more cautiously—postponing investments, cutting discretionary spending, and reducing costs (Bloom, 2014). The first column of Table 7 illustrates that a one standard deviation increase in TAV is related to a 0.026% reduction in the profitability ratio over a quarter. Taken to dollar terms, the effect size suggests a 1.65 million dollar decrease in profitability. A larger dollar fall in revenue than in profitability aligns with standard models of firm behavior under uncertainty or negative shocks, where managers actively adjust costs to partially offset revenue losses and stabilize profitability.

The remaining columns of both tables show the effects of TAV on these ratios for each of the 12 Fama-French sectors, as well as the construction and transportation sectors. We observe a significant negative relationship between TAV and the two ratios for the Business Equipment, Construction, Manufacturing, Money (finance and insurance), Consumer Non-Durables, and Retail Shops. Industries such as Business Equipment and Manufacturing are capital-intensive and are sensitive to supply chain disruptions. The larger decline in revenues relative to profitability suggests that climate disruptions directly reduce production and sales volumes; however, firms partially offset shocks by cutting costs or adjusting variable inputs. The outsized effect on profitability relative to revenues in the construction sector reflects the stabilizing role of long-term contracts, which anchor revenues in the short run. However, firms absorb extra costs—such as higher labor expenses due to delays—that they cannot fully pass through, eroding profitability.

For non-durables and retail shops, both revenue and profitability reflect negative exposure to temperature volatility. The business models in these industries rely on high sales volume with low margins, and adverse or unpredictable weather can directly reduce consumer demand and alter purchasing patterns, resulting in lower sales. Unlike industries with long-term contracts, non-durables and retail face contemporaneous revenue shocks as shoppers

reduce or postpone purchases in unfavorable weather.

Similarly, in the Finance and Insurance sector, more acute temperature variations correlate with more frequent and severe climate hazards and disasters, and may increase claims unpredictably for 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 conditions.[12]

In contrast, we observe a positive and significant relationship between TAV and revenues for Utilities, but this effect does not extend to profitability. The institutional details for utilities are unique due to their regulatory constraints. Firms charge a single rate per unit of energy which is approved periodically by regional public utility commissions based on projected usage and costs. This rate structure suggests that during periods of increased temperature extremes, demand may rise—leading to higher total revenues.[13] However, because the rate is fixed and cannot be quickly adjusted to reflect unexpected spikes in operational costs (e.g., for fuel procurement or emergency maintenance), utilities will face higher expenditures that are not offset by proportional increases in pricing.

We also detect a positive relationship between revenue, income and TAV in the energy industry (oil, gas, and coal extraction). 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 Section 4.3. To determine whether consumption or production channels are driving the over- or underperformance of firms in more temperature-volatile

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

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

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 Section 4.3.1, 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 7. 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 Section 4.3.2, 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.

4 Explanations

In this section, we test whether behavioral responses, uncertainty frictions, or real economic shocks drive the negative relation between abnormal temperature volatility and firm performance.

4.1 Beliefs & attention

4.1.1 Beliefs

A key economic mechanism through which temperature affects asset prices is the updating of agents' beliefs. Bakkensen and Barrage (2022) and Bernstein et al. (2019) show how beliefs regarding flood risk are transmitted to asset prices in the mortgage market. (Deryugina, 2013) presents evidence that realized extreme temperatures serve in shaping beliefs about the climate; however, this effect is heterogeneous and appears only among conservatives, suggesting that ideological and personal priors can entrench beliefs and limit the updating process.

We distinguish between two conceptually distinct forms of belief. The first is in the existence of climate change as a phenomenon; the second—likely conditional on the first—is the belief that one has personally experienced the harmful effects of climate change. Survey evidence from the Yale Program on Climate Change Communication spanning 2010 to 2019 (Marlon et al., 2022) makes the divergence clear. While roughly two-thirds of Americans acknowledge that global warming is occurring, only about one-third report that they have experienced its effects. This wedge is striking given the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (Stocker et al., 2013), which determined that changes in many extreme weather and climate events have been observed since 1950. Indeed,

a new line of scientific research, attribution science, has emerged to quantify the extent to which specific weather events have been exacerbated by climate change (Stott et al., 2016).

How can we reconcile agents' recognition of climate change—and empirical evidence that it has already intensified extreme weather—with a widespread lack of perceived personal exposure or harm? Gennaioli et al. (2015) offer a theoretical explanation that departs from rational Bayesian updating. Agents systematically underweight the probability and relevance of rare events unless recent experiences make such risks salient. As a result, agents may acknowledge the reality of climate change at an abstract level while underestimating their own exposure or vulnerability until the materialization of a salient event prompts a reassessment.

To analyze the relationship between beliefs and abnormal temperature volatility, we use survey data on climate change risk perceptions from the Yale Program on Climate Change Communication. Specifically, we collect state-year level data from 2010 to 2019 on the percentage of respondents answering "Yes" to the following questions: (a) whether they believe climate change is happening; (b) whether they somewhat or strongly agree that they have personally experienced the effects of global warming; and (c) whether they think global warming will harm people in the US a moderate amount or a great deal. We calculate the unexpected change in each series by obtaining residuals from AR(1) models at the state level. We then regress these innovations on TAV, state-level economic indicators, and a set of other relevant physical risk variables. We also include year and state fixed effects to control for unobserved common shocks, leaving spatial variation.

Local attention is proxied using innovations in state-level Google search data for the topic "Climate Change". Heightened attention may drive information acquisition about climate change, yet does not necessarily result in updated beliefs. Makridis and Schloetzer (2023) and Choi et al. (2020), for example, document that extreme temperatures impact individuals' attention by 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), and Sautner et al. (2023)). Survey evidence reveals belief forma-

tion by capturing what individuals report experiencing, while attention indices reflect what individuals choose to investigate, not explicitly what they believe.

Table 8 reports these regression results. The first four columns correspond to question (a), the next four to question (b), and the final four to question (c). Abnormal temperature volatility appears to be unrelated to the unexpected share of respondents expressing their belief in global warming. One reason for the lack of a significant relationship may be that TAV aggregates both unusually cold and hot observations, diluting the effect. As Deryugina (2013) shows, exposure to unusually cold days reduces belief in global warming more strongly than exposure to unusually warm days increases it. Another likely explanation is that political polarization dominates individual beliefs about global warming, limiting the influence of local weather shocks (McCright et al., 2014).

Turning to column (5), we find that a one-standard deviation increase in TAV is associated with a 0.46 percentage point unexpected increase in the share of respondents that believe that they have been exposed. Column (9) shows a positive, though smaller, association (0.23 percentage points) for the belief that global warming will harm people in the US. These results imply that respondents interpret abnormal temperature volatility as evidence of personal exposure and broader harm from climate change. The finding is consistent with Gennaioli et al. (2015), in that salient events prompt agents to update their beliefs about risks that are otherwise underweighted.

Overall, the association survives inclusion of other physical risks, state economic variables, and state and year fixed effects. The third row of Table 8 reveals a negative association between temperature anomalies (TA) and beliefs. In a Bayesian framework, extreme weather events should update beliefs, yet TA may not sufficiently capture these salient shocks. Moreover, in an environment where agents have memory, a lack of extreme anomalies may lead individuals to gradually discount or neglect climate risks over time, further weakening the relationship. Finally, I show that innovations in the topic "Climate Change"' are positively and, in most cases, significantly related to all dependent variables. Attention, therefore, may

reflect exposure to new information or heightened salience, but does not necessarily represent a one-to-one translation into updated beliefs.

4.1.2 Attention

Although often conflated, belief and attention represent distinct concepts. Belief reflects an agent's mental probability distribution, an expectation or conviction regarding whether an aspect of climate change is real or personally relevant. Attention, proxied by observable behaviors such as Google search intensity, can capture salience, and information acquisition—distinct from and not always translating into belief change.

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 determinant of demand for attention to climate change (Engle et al. (2020)) and analysts' attention to firm-specific climate exposure (Sautner et al. (2023)).

Google search activity serves as a proxy for investor attention and sentiment (Da et al. (2011); Choi et al. (2020)). Retail investors often increase searches on climate topics in response to perceived risks, reflecting rising concern or interest that can influence behaviors. While institutional investors rely more on proprietary data, they remain attentive to shifts in public sentiment and media coverage, using search trends as signals of climate risk salience. This, in turn, can prompt institutional investors to consider these factors in their own investment strategies, albeit to a lesser extent than retail investors.

To test whether the metrics are related to unexpected changes in investor behavior, 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.

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

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

The estimated coefficients across various specifications are presented in Table 9. Regardless of controls and fixed effects, TAV appears to explain explain unanticipated state-level Google search interest for the topic "Climate Change". We find a negative coefficient on average temperature anomalies, TA. Colder-than-normal temperatures prompt an increase in public information gathering on climate change, consistent with Moore et al. (2019), who show that cold shocks drive larger increases in social media discussion than equally sized heat shocks.

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, representing the association between unexpected national news and TAV. To create a US-level time series for temperature, we aggregate TAV by taking the population weighted value across all states:

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

where ρ_t is a time fixed effect.[14]

[14]Calculating a simple correlation between weighted TAV and the innovations in the WSJ news index

Table 10 reports the estimated coefficients. Unexpected changes in national attention to climate change remain positively associated with TAV, after controlling for other climate variables and quarter fixed effects. The coefficients are large but less significant than for regional attention, consistent with our construction of TAV at the state level. Taken with the regional results, these findings show that TAV correlates strongly with unexpected increases in climate-related news coverage, underscoring the impact of temperature variability on public and investor awareness.

The evidence thus far suggests that temperature variability spurs retail investor attention and prompts news agencies to publish articles on 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 climate risks faced by the firm, as mentioned by analysts, investors, and managers in each call.

We use the 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 climate change risks, hereafter $CCExposure$. Their methodology involves using climate-related bigrams (i.e., two-word combinations) to sift through sentences and measure the discussion of climate topics as a fraction of all other topics. While the universe of bigrams used in Sautner et al. (2023) does not perfectly match the risks captured by TAV, there is sufficient similarity between these metrics and $CCExposure$ to make a meaningful comparison.

Our empirical specification regresses yearly firm level $CCExposure$ on TAV with industry fixed effects, γ_{ind}:

$$CCExposure_{i,t} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * D_{i,t-1} + \beta_3 * WSJ_{s,t} + \gamma_{ind} + \epsilon_{i,s,t}. \tag{8}$$

for firm i at year t headquartered in state s. The firm-level control variables, $D_{i,t-1}$, include log of total assets, leverage, log book-to-market equity, Tobin's Q, return-on-assets, and log

yields a Pearson coefficient of 19.75%, indicating a moderate positive relationship with the index.

of plant, property, and equipment over assets. Generally, we use the one-year lag of every variable as they may be influenced by temperature at time t. We include the innovations of the WSJ news index (WSJ_t) to distinguish the attention effects from the direct physical impacts of temperature faced by the firm.

Table 11 presents statistically significant associations with TAV and firm-specific attention to 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 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 level. This suggests that temperature variability is a contributing factor in participants' concerns regarding 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. Notably, other weather shocks have a muted effect on discussions during earnings calls.

This analysis suggests that abnormal temperature variability TAV explains heightened and unanticipated attention to climate change, driving the demand for additional information about climate change. However, there are broader implications of these results for the financial literature. Many papers rely on belief update shocks—either through direct temperature effects (see Choi et al. (2020) or Alekseev et al. (2021)) or through media attention (Engle et al., 2020), which is plausibly influenced by unusual weather—to understand how trading behavior changes as a result of climate risks.[15] However, there is evidence that unusual temperatures are becoming normalized to the broader public as they are repeatedly exposed (Moore et al., 2019). Our findings reveal that certain characterizations of the temperature anomaly distribution are ineffective in changing the behavior of investors and, ultimately, asset prices. Intuitively, the results suggest that researchers should be selective in the metrics

[15]Physical risks can be considered as 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. For an extensive review on belief updating in the climate finance literature, see Giglio et al. (2021).

they apply to study market responses to climate.

4.2 Uncertainty

Our evidence thus far points to increased uncertainty in financial markets with abnormal temperature volatility. Firms respond by cutting costs, consistent with increased economic uncertainty as documented by (Bloom, 2014). In addition, investors revise beliefs about climate damages, which can drive greater price dispersion (Baldauf et al., 2020). In this section, we test whether realized temperature volatility is associated with firm-specific idiosyncratic volatility and dispersion in analyst forecasts.

4.2.1 Idiosyncratic volatility

We use Fama-MacBeth regressions to estimate the average contemporaneous cross-sectional relationship between abnormal temperature volatility and idiosyncratic volatility. For each stock and month, idiosyncratic volatility is measured as the standard deviation of residuals from regressing daily log returns on the Fama-French 3-factor model. Log returns mitigate the positive skewness in stock returns, which would otherwise induce a spurious correlation between the realized mean returns and realized variance Ang et al. (2009). The logarithm of this monthly standard deviation serves as the main measure of firm-specific idiosyncratic volatility.

Control variables largely remain the same as the ones used in Section 3.2, with the addition of lagged returns, lagged idiosyncratic volatility, and changes in the VIX index from the Chicago Board Options Exchange (Ang et al., 2006). Including changes in the VIX captures shocks to aggregate market volatility, while lagged terms account for the persistence commonly observed in idiosyncratic volatility(Ang et al., 2009). We also include quarterly contemporaneous dispersion in analyst forecasts (Diether et al., 2002), which helps separate the effects of temperature volatility that operate through belief heterogeneity from those reflecting uncertainty about temperature-driven damages. This control introduces endogeneity

concerns, since TAV may both increase forecast dispersion and, through it, affect idiosyncratic volatility. Analyst forecast data are from I/B/E/S, and we use the natural log of the forecast standard deviation. Adding analyst dispersion restricts the sample to larger firms, where idiosyncratic volatility effects are attenuated due to greater analyst coverage.

Table 13 reports the results of the Fama-MacBeth regressions. The positive coefficients on abnormal temperature volatility in the first row show that, in a given month, firms facing larger temperature shocks experience higher idiosyncratic volatility. the association survives inclusion of lagged volatility, the VIX index, and lagged returns. According to the first column, a one-standard deviation increase in temperature volatility raises the natural log of idiosyncratic volatility by 0.062, or about 6.4% in percentage terms. The standard deviation of log idiosyncratic volatility in the sample is 0.650, so the effect of a temperature volatility shock is roughly a tenth of the cross-sectional variation in log idiosyncratic volatility.

Column (5) of Table 13 presents no relationship between other physical risk metrics and idiosyncratic volatility. In column (6), innovations in the WSJ news index have a positive and significant effect, indicating that unexpected climate news raises price dispersion, likely via a belief channel in line with Baldauf et al. (2020). Analyst dispersion is also positively related as shown in column (7)—a one-standard deviation increase in the log of analyst dispersion raises idiosyncratic volatility by 4%. Finally, Column (8) includes both contemporaneous and lagged TAV, showing no relationship with lagged temperature volatility.

Taken together, cross-sectional return volatility unexplained by the Fama-French 3-factor model rises with abnormal temperature volatility. This highlights a role for uncertainty about the recognition and attribution of firm-level damages during temperature-related shocks. Unlike the persistent volatility documented by Kruttli et al. (2025) after discrete events like hurricanes, where damages are certain but their magnitude is unknown, the uncertainty caused by TAV is resolved within the period. For abnormal temperature volatility, both the scale and existence of firm damages are uncertain and dependent on beliefs, highlighting the informational and interpretive challenges this risk creates.

Beliefs may also encourage stratified returns. Disagreement among analysts likely reflects differences in opinion or beliefs, rather than pure uncertainty Diether et al. (2002). In this context, agents hold divergent views on the magnitude and consequences of climate-related impacts. This divergence is consistent with findings from the Yale Climate Opinions Survey, where only half of those who believe in climate change also believe they have personally experienced its negative effects. Because the specification is contemporaneous, we cannot disentangle whether analyst dispersion is driven by differing beliefs or information. In the next section, we interrogate this explanation by examining how analysts process abnormal temperature volatility into their earnings forecasts.

4.2.2 Analyst forecasts

We next test the relationship between temperature volatility and market uncertainty through analyst forecasts. Diether et al. (2002) argue that dispersion in analysts' forecasts proxies for differences in investor opinion. Analyst forecasts provide a useful measure of whether disagreements across market participants widen and whether analysts accurately anticipate the impact of these shocks on firm performance.

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 3.3. We study the relationship between abnormal temperature volatility and earnings surprises by estimating the following regression model using pooled ordinary least squares:

$$\mathrm{Y}_{i,t} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * X_{i,t-1} + \beta_3 * D_{s,t} + \beta_4 * \text{Analysts}_{i,t} + \gamma_{\text{i, year}} + \varepsilon_{it} \qquad (9)$$

where the dependent variable is either the natural log of the standard deviation of analyst earnings-per-share (EPS) forecasts or the quarterly earnings surprise divided by the prior quarter's stock price. Each variable is constructed for firm i and quarter t. The firm-level control variables, $X_{i,t-1}$, lagged by one quarter, include log of total assets, leverage, log book-

to-market equity, Tobin's Q, return-on-assets, and log of plant, property, and equipment over assets. $D_{s,t}$ are a vector of state economic variables: the house price index, personal income, and the unemployment rate all transformed to a year-over-year growth. $\text{Analysts}_{i,t}$ represent the number of analysts producing the quarterly earnings forecast for the firm. γ represents firm by year fixed effects.

The first five columns of Table 12 report results using the standard deviation of analyst EPS forecasts as the dependent variable. Across these columns, TAV is positively associated with greater dispersion among analyst forecasts; however, inclusion of firm by year fixed effects erodes the statistical power of the relationship. The result indicates that increases in TAV for a given firm are associated with contemporaneous increases in analyst forecast dispersion for that same firm, relative to its own historical average. According to the first column, a one-standard deviation increase in TAV increases the dispersion of earnings forecasts by about 2%. In economic terms, temperature volatility shocks lead to modest but measurable increases in analyst disagreement, with the effect size comparable to about 2% of the standard deviation in forecast dispersion. The fifth column shows that lagged TAV has no statistically significant effect on analyst forecast dispersion.

The last five columns of Table 12 use the quarterly earnings surprise divided by the lagged stock price multiplied by 100 as the dependent variable. Column (6) indicates a one-standard deviation increase in TAV is related to a 0.03 reduction in the scaled earnings surprise, about 5.2% of the mean of the variable. Negative EPS surprises mean that, on average, realized firm performance is systematically worse than expectations. The results align with Pankratz et al. (2023), which indicate that increases in firms' heat exposure are related with more negative revenue and income surprises.

Collectively, the findings offer a nuanced picture. Both retail and institutional investors become more attentive to TAV, suggesting active information acquisition and belief updating. However, uncertainty remains about the true impact of abnormal temperature volatility on firm fundamentals. The transitory uncertainty is reflected in rising realized idiosyncratic

volatility and dispersion in beliefs among analysts although to a lesser extent. While some analysts are attentive, they struggle to fully account for the impact of TAV in their forecasts leading to a modest underestimation of damages. The results fit within a broader framework of uncertainty-induced frictions and heterogeneous beliefs, where uncertainty about real effects from damages (Kruttli et al., 2025) and, to a lesser extent, belief heterogeneity (Baldauf et al., 2020) contribute to greater return dispersion.

How should this greater uncertainty appear in the negative contemporaneous relationship between TAV and returns? The empirical literature is mixed: Ang et al. (2009) report a negative idiosyncratic volatility–return relation, while Fu (2009) finds a modest positive correlation. Our data show an almost flat relationship, with a correlation of –0.03. The positive association between temperature volatility and idiosyncratic volatility, alongside the negative relation between temperature volatility and returns, points to heightened uncertainty about damages. Two non-mutually exclusive channels—objective uncertainty and disagreement among investors, possibly amplified by ambiguity aversion—drive this effect, placing downward pressure on returns as temperature volatility rises. In this context, elevated idiosyncratic volatility reflects unresolved, priced uncertainty that acts as a drag on realized stock performance.

This dynamic differs from the results in Kruttli et al. (2025), where the market eventually prices hurricane exposure more accurately, leading to a positive premium for vulnerable firms later in their sample. In contrast, investors appear to view shocks from TAV as transitory, discounting prices in the short run but not sustaining a long-term volatility or risk premium once the uncertainty resolves.

4.3 Economic

We document a channel of real impact where firms have lower profitability and cut costs under the strain of abnormal temperature volatility. To understand the mechanism, we examine both demand and supply channels. On the demand side, data from the US Consumer

Expenditure Survey show that aggregate demand falls with higher TAV, though the effects vary by industry. On the supply side, the American Time Use Survey and labor statistics reveal that workers in temperature-sensitive industries log fewer hours with temperature volatility.

4.3.1 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 metric to re-examine the relationship between temperature and consumer expenditure, as well as between temperature and electricity demand. This approach allows us to test whether TAV helps explain variation in aggregate demand, and by extension, firm performance.

We collect data from the Consumer Expenditure Survey (CEX) from 1994 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 family income. 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 20,779 household interviews per annum across 43 states, though this number

declined to 12,975 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 14. These expenditure categories serve as the primary dependent variables in our empirical tests, following the specification:

$$Expenditure_{h,s,t} = \alpha + \beta_1 * TAV_{s,t} + \beta_2 * D_{h,t} + \beta_3 * Q_{s,t} + \rho_t + \gamma_{s,y} + \epsilon_{h,s,t}, \quad (10)$$

where $Expenditure$ represents the log of the dollar amount household h in state s spent on a category in the three months preceding interview period t. The temperature variable, TAV, captures the abnormal temperature volatility over the preceding three months in state s. The vector X includes household-specific continuous covariates, which are detailed in Table 15, 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 the number of earners in the household, 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 by quarter fixed effects 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 by year fixed effects, represented by $\gamma_{s,y}$, control for unobserved state by year characteristics. The specification focuses on the variation within states over time, with state-level clustering used to account for treatment effects.

Table 16 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 0.46% reduction in total expenditure. For scale, an additional household member correlates with a 4% 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 $43,244, would reduce spending by approximately $199 per year. For the 42,248 surveyed

households in Texas, this implies a potential aggregate expenditure decrease of over $8 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 nearly $2 billion under similar deviations in temperature variability.

Consistent with our findings in Section 3, we observe substantial heterogeneity across expenditure categories. Specifically, there is a significant positive relationship between TAV and electricity spending, paralleling the positive effect of TAV on profitability observed in our industry-level analysis. This result suggests that households' sensitivity 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 electricity usage, mirroring the observed decline in returns during periods of higher-than-usual temperatures in our revenue analysis. Table 16 also 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 3.3, which indicate widespread declines in cash flows across sectors, particularly within the non-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 and, in turn, firm performance. 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 many categories. This broad applicability underscores the utility of TAV for assessing firms' exposure to temperature variability across various industries. As argued in Section A.2, incorporating TAV into climate risk reporting will allow investors to better understand the potential financial impacts of temperature fluctuations on their stock investments.

4.3.2 Labor

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 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.

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 ser-

vices, 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 17 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 2.9 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 cycle.

5 Conclusion

Climate scientists have established that the distribution of temperature anomalies is broadening, with a pronounced lengthening of its tails (Hansen et al., 2012). Climate change is also accelerating transitions between temperature extremes (Wu et al., 2025). Motivated by these empirical facts, we construct a metric defined as the deviation of unconditional volatility from its historical norm. Exploiting this phenomenon in the cross-section yields substantial abnormal returns.

We tie this abnormal return to multiple economic mechanisms: lower sales, reduced labor productivity, and increased investor uncertainty. Investor behavior adjusts as temper-

ature volatility rises, with heightened information-seeking and belief updating, reflected in both greater attention and increased idiosyncratic volatility.

These results reconcile prior mixed evidence on the pricing of temperature shocks. Market participants appear myopic to gradual shifts in climate. Variations in the mean of temperature anomalies, as well as other phenomena such as precipitation and wildfire risk, exhibit little contemporaneous effect on firm outcomes.

These findings have implications for policymakers and investors, given the increased global demand for consistent and comparable climate risk disclosure (Carattini et al., 2022). Our metric offers a practical approach to measuring physical climate risk exposure using transparent, public data. In the Internet Appendices 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 outline a method to help investors evaluate the exposure of companies within their portfolios over a relevant future time horizon and adjust their allocation to minimize portfolio exposure.

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6 Figures

Figure 1: Geographic concentration of firms in the US 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.

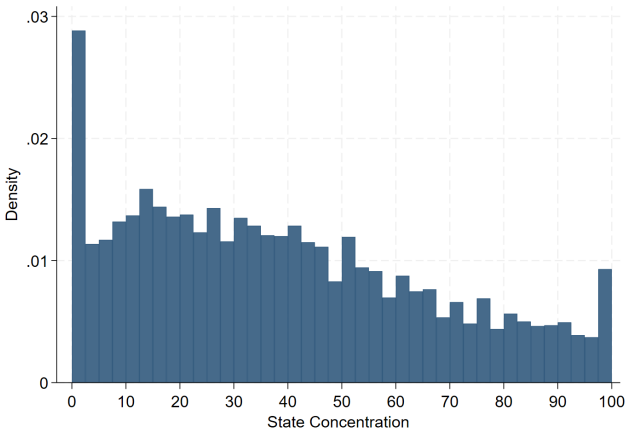


Figure 2: US revenue concentration of firms based on Compustat segments

This histogram shows a left-skewed distribution of US revenue concentration, indicating a range of domestic and international sales exposure among firms. We remove values at 100% for clarity as these values are about 22% of the data. We set a 73% threshold, corresponding approximately to the 10th percentile, to exclude firms with significant sales outside the US.

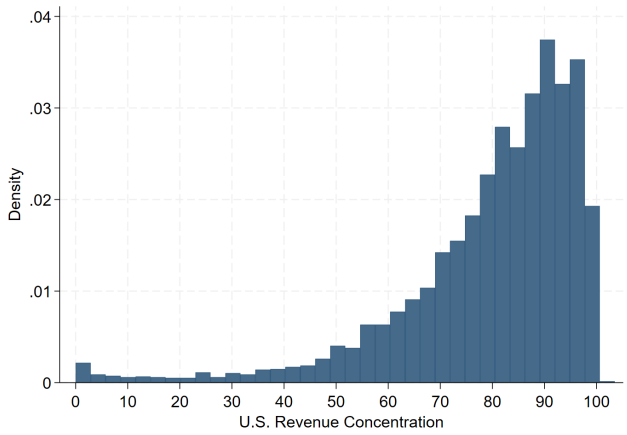


Figure 3: Unadjusted long-short returns of portfolios sorted on TAV

This figure presents the long-short portfolio returns sorted on US state exposure to variability of temperature anomalies (TAV). The long-short portfolio methodology consists of sorting 48 states into exposure quartiles (yellow) or quintiles (blue) for a given month. We calculate the average value-weighted returns of firms headquartered in the states assigned to each of the exposure portfolios. Each line is therefore the monthly difference between the average return in the most versus least vulnerable portfolio based on TAV.

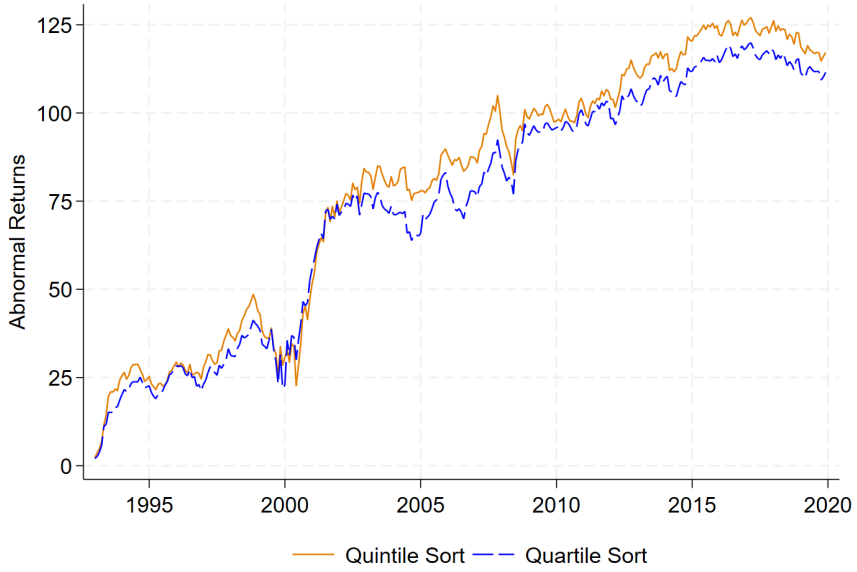
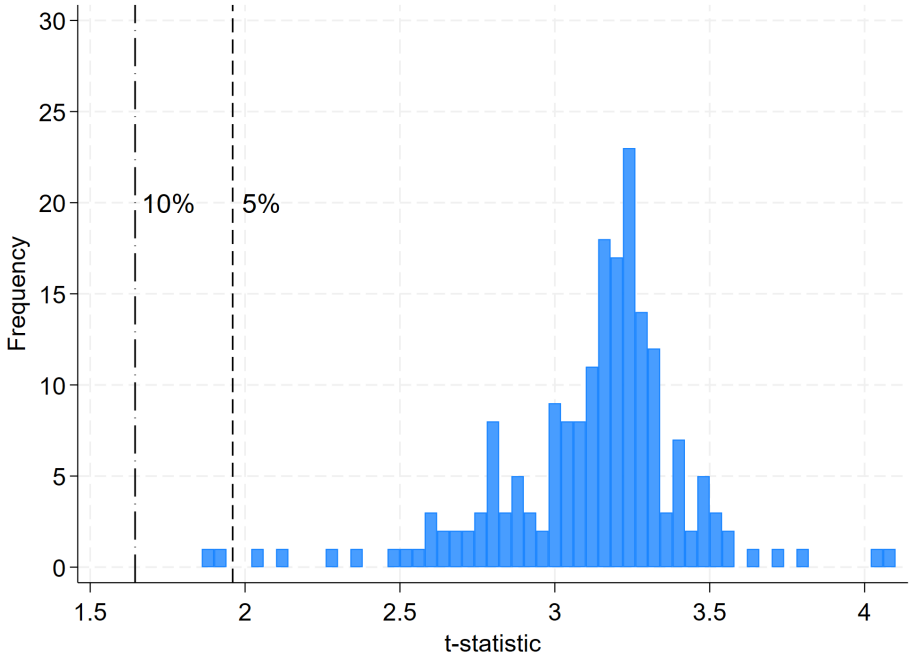


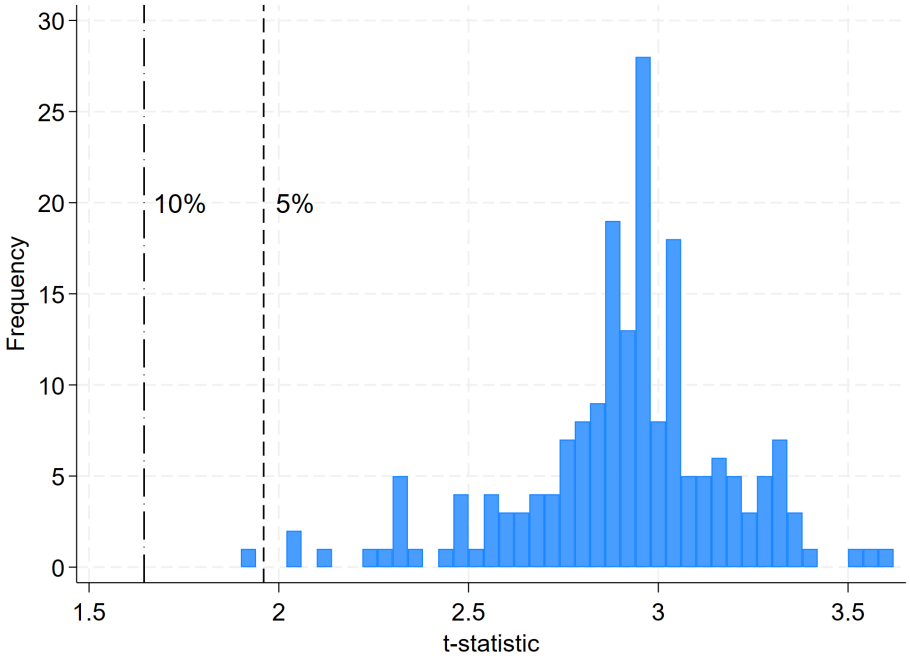
Figure 4: Alpha t-statistics

This figure displays histograms of t-statistics from regressions of long-short portfolio returns (sorted by quartile and quintile) on the Fama-French 3-factor model, each time including one of 189 anomaly predictors from Chen and Zimmermann (2021). The vertical dashed lines indicate significance thresholds at the 10% and 5% levels after adjusting for multiple testing using the Benjamini-Hochberg procedure for the False Discovery Rate.

(a) Quartile Sorts



(b) Quintile Sorts



7 Tables

Table 1: Summary Statistics

This table presents summary statistics used in the paper. Each variable panel describes the frequency and whether the variable is at the US state level or US level. Firm or household level variables such as returns or expenditures are winsorized at 1%. Table 18 in the Appendix presents variable definitions.

Variable	Mean	STDV	P10	P25	Median	P75	P90	N
Panel (A): State Monthly Variables								
TAV	0.293	(2.005)	-2.158	-0.939	0.273	1.562	2.778	15,552
TA	-0.032	(0.716)	-0.847	-0.478	-0.080	0.362	0.851	15,552
Precipitation	0.060	(1.310)	-1.378	-0.691	-0.071	0.653	1.609	15,552
Burning	0.800	(5.596)	-5.451	-2.533	0.487	3.785	7.473	15,552
Panel (B): Compustat/IBES Firm Quarterly and Yearly Variables								
Leverage	0.210	(0.201)	0	0.033	0.161	0.333	0.493	349,087
Income/L1.Assets	0.020	(3.858)	-3.583	-0.122	0.487	1.725	3.143	336,268
Revenues/L1.Assets	24.866	(21.124)	1.904	7.735	20.878	35.929	53.433	336,288
Total Assets, ln	6.019	(1.974)	3.451	4.547	5.957	7.345	8.691	345,561
Bk to Mkt, ln	-0.637	(0.777)	-1.683	-1.096	-0.554	-0.114	0.262	333,543
ROA	-1.347	(41.453)	-38.559	-1.698	4.635	16.571	30.077	345,543
Tobin's Q	1.791	(1.318)	0.954	1.041	1.3	1.996	3.251	344,529
PPE/Assets, ln	-2.244	(1.399)	-4.296	-3.341	-2.004	-1.103	-0.497	339,493
Forecast Dispersion, ln	-3.871	(0.947)	-5.111	-4.605	-3.918	-3.219	-2.563	183,140
Mean Surprise/L1.Price, %	0.639	(5.073)	-1.286	0.442	1.21	1.823	2.517	223,358
CC Exposure	0.925	(2.486)	0	0.091	0.262	0.642	1.833	123,402
Compustat Concentration	92.045	(14.806)	73.125	88.892	100.000	100.000	100.000	11,829
Near Headquarters	0.388	(0.274)	0.049	0.160	0.348	0.578	0.804	11,829
Panel (C): State Quarterly Variables								
TAV	-0.037	(0.452)	-0.586	-0.325	-0.059	0.232	0.542	5,040
TA	0.303	(1.342)	-1.340	-0.529	0.291	1.126	1.950	5,040
Precipitation	0.065	(0.829)	-0.882	-0.441	-0.006	0.493	1.101	5,184
Burning	0.791	(4.365)	-4.023	-1.728	0.567	3.088	5.895	5,184
HPI, yoy	0.036	(0.051)	-0.023	0.012	0.039	0.058	0.091	5,184
Income, yoy	0.046	(0.065)	0.011	0.031	0.048	0.064	0.081	5,184
Unrate, yoy	-0.009	(0.195)	-0.167	-0.115	-0.057	0.029	0.196	5,184
Google SVI, Innov	0.000	(12.015)	-11.273	-6.988	-2.212	4.093	13.305	3,024
Panel (D): State Yearly Variables								
TAV	-0.052	(0.273)	-0.383	-0.236	-0.065	0.114	0.300	1,296
TA	0.292	(0.792)	-0.704	-0.237	0.286	0.861	1.279	1,296
Precipitation	0.062	(0.428)	-0.42	-0.181	0.034	0.270	0.613	1,296
Burning	0.795	(2.831)	-2.384	-0.830	0.735	2.286	4.022	1,296
HPI, yoy	0.036	(0.051)	-0.022	0.011	0.039	0.057	0.091	1,296
Income, yoy	0.046	(0.062)	0.007	0.031	0.048	0.064	0.081	1,296
Unrate, yoy	-0.009	(0.187)	-0.161	-0.114	-0.056	0.032	0.232	1,296
Google SVI, Innov	0.000	(9.793)	-8.407	-5.988	-3.499	2.828	11.689	750
Yale Exposure, Innov	-0.802	(3.802)	-7.076	-2.853	-0.083	1.828	3.332	432
Yale Happening, Innov	-0.569	(2.636)	-3.932	-2.584	-0.515	1.288	2.893	432
Yale Harm, Innov	-0.319	(3.820)	-6.552	-2.689	0.470	2.517	3.855	432
Population	5909.386	(6,540.109)	811.63	1713.82	4146.698	6797.484	12599.84	1,350
Panel (E): CRSP Monthly								
Returns, %	0.734	-13.794	-14.799	-6.25	0.127	6.897	16.049	1,123,307
Idiosyncratic Volatility	0.031	-0.023	0.01	0.015	0.024	0.04	0.061	1,121,451

This table continues the summary statistics.

Panel (F): Time Series Monthly Variables								
Variable	Mean	STDV	P10	P25	Median	P75	P90	N
Mkt-RF	0.683	(4.224)	-4.83	-1.885	1.24	3.385	5.58	324
SMB	0.133	(3.040)	-3.42	-1.825	0.1	2.01	3.59	324
HML	0.168	(3.034)	-3.17	-1.645	0.04	1.665	3.53	324
RMW	0.302	(2.711)	-2.04	-0.765	0.355	1.27	2.89	324
CMA	0.236	(2.030)	-1.89	-1.02	0.02	1.345	2.94	324
BAB	0.836	(3.904)	-2.94	-0.6	0.93	2.46	5.2	324
MOM	0.450	(4.874)	-4.79	-1.385	0.495	2.98	5.28	324
LIQ	0.438	(3.650)	-3.672	-1.607	0.319	2.752	4.828	324
RF	0.198	(0.173)	0	0.01	0.16	0.385	0.43	324
VIX	19.182	(7.704)	11.976	13.5	17.29	22.797	28.134	324
CPI	0.184	(0.332)	-0.167	0	0.19	0.39	0.562	324
Panel (G): Time Series Quarterly Variables								
TAV, Pop	0.315	(0.828)	-0.653	-0.286	0.258	0.88	1.298	108
TA, Pop	-0.027	(0.243)	-0.288	-0.176	-0.049	0.079	0.295	108
Precipitation, Pop	0.067	(0.371)	-0.369	-0.219	0.022	0.29	0.572	108
Burning, Pop	0.901	(2.190)	-1.578	-0.37	0.992	2.296	3.888	108
WSJ, Innov	0.000	(0.001)	-0.001	-0.001	0	0	0.001	98
Panel (H): American Time Use Survey								
Age	42.973	(13.463)	26	33	42	53	61	130,058
Children	0.951	(1.134)	0	0	1	2	2	130,058
White	0.695	(0.460)	0	0	1	1	1	130,058
College Degree	0.391	(0.488)	0	0	0	1	1	130,058
High School Grad	0.235	(0.424)	0	0	0	0	1	130,058
Cohabitating	0.589	(0.492)	0	0	1	1	1	130,058
Full-Time Emp	0.788	(0.408)	0	1	1	1	1	130,058
Sex	0.491	(0.500)	0	0	0	1	1	130,058
Self Emp	0.112	(0.316)	0	0	0	0	1	130,058
Day of Wk	2.979	(2.348)	0	0	3	5	6	130,058
Family income	10.873	(4.418)	4	9	12	14	15	130,058
Panel (I): Bureau of Labor Statistics: Public Use Microdata								
Total Expenditure, ln	9.077	(0.704)	8.153	8.6	9.086	9.56	9.991	531,469
Non Durables, ln	7.922	(0.680)	7.017	7.482	7.954	8.393	8.779	530,966
Durables, ln	5.541	(1.827)	3.296	4.248	5.416	6.713	7.961	312,652
Electricity, ln	5.534	(0.708)	4.615	5.106	5.598	6.04	6.397	498,369
Health Care, ln	6.441	(1.209)	4.878	5.71	6.562	7.291	7.877	427,276
Entertainment, ln	5.759	(1.101)	4.431	5.124	5.796	6.494	7.123	478,589
Aparrel, ln	5.274	(1.210)	3.638	4.554	5.403	6.146	6.726	422,475
Family Income, before tax	10.396	(1.265)	8.985	9.852	10.605	11.225	11.695	423,488
Age	49.002	(16.080)	28	36	48	61	72	540,260
Rooms	5.839	(2.005)	3	4	6	7	8	527,467
Family Size	2.573	(1.499)	1	1	2	4	5	540,260
Earners	1.337	(0.931)	0	1	1	2	2	537,595
Sex	1.493	(0.500)	1	1	1	2	2	540,260
Urban	1.014	(0.116)	1	1	1	1	1	540,260
Marital Status	2.247	(1.578)	1	1	1	3	5	540,260
Education	12.795	(2.807)	11	12	13	15	16	540,260
Race	1.308	(0.807)	1	1	1	1	2	540,260
Housing Tenure	2.286	(1.336)	1	1	2	4	4	540,260

Table 2: Transition Matrices for TAV: Quartile (A) Quintile (B)

This table illustrates the frequency of states moving from one quartile or quintile of exposure to another. Panel A represents the transition matrix of the portfolio strategy when using TAV using quartile sorts. Panel B uses quintile sorts. The sample period is 1993–2019. The left most column of each panel is the beginning exposure quintile or quartile of the state. The other columns represents the exposure percentile of the state in the next month. Each number represents the percent of times a state moves from one percentile to another.

Panel A: Quartile Portfolio

	Rebalanced Quartile			
	1	2	3	4
1	35.91	25.93	20.54	17.62
2	25.46	27.81	25.28	21.44
3	21.08	25.57	27.50	25.85
4	17.54	20.69	26.68	35.09
Total	100	100	100	100

Panel B: Quintile Portfolio

	Rebalanced Quintile				
	1	2	3	4	5
1	31.83	23.47	15.91	16.04	12.76
2	22.66	23.81	18.89	20.03	14.61
3	18.54	21.67	20.09	21.81	17.89
4	16.32	19.29	21.46	23.75	19.20
5	13.90	15.48	17.41	22.84	30.37
Total	100	100	100	100	100

Table 3: Abnormal returns to portfolios sorted on TAV

This table reports average monthly excess returns for portfolios sorted by firm exposure to differences in the standard deviation of temperature anomalies, abnormal temperature variability (TAV). Each month t, we sort U.S. states into four or five groups based on their realization of 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 TAV (low variability). Portfolios 4 or 5 include those firms in states experiencing the highest values of TAV (high variability). We group the middle portfolios together by equal-weighting their respective returns and denote them as either "Portfolios 2,3" or "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for combinations of the Fama-French 3, liquidity, betting against beta, momentum, and the Fama-French 5 factors. "Portfolio 1–5" or "Portfolio 1–4" reports the return difference between the least and most exposed portfolios. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. The sample period is from January 1993 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 12 lags.

Panel A: Quartile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.215**	0.178**	0.190**	0.179*	0.160**
	(0.108)	(0.087)	(0.086)	(0.093)	(0.077)
Portfolios 2, 3	0.071	0.020	0.002	-0.103	-0.089
	(0.098)	(0.067)	(0.064)	(0.059)	(0.069)
Portfolio 4	-0.169	-0.183	-0.176	-0.188	-0.183
	(0.071)	(0.075)	(0.070)	(0.074)	(0.080)
Portfolio 1 - 4	0.383***	0.362***	0.366***	0.367***	0.343***
	(0.130)	(0.112)	(0.107)	(0.112)	(0.114)

Panel B: Quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.230**	0.189**	0.202**	0.189**	0.169**
	(0.108)	(0.085)	(0.085)	(0.091)	(0.076)
Portfolios 2, 3, 4	0.078	0.028	0.011	-0.090	-0.080
	(0.111)	(0.065)	(0.064)	(0.049)	(0.059)
Portfolio 5	-0.171	-0.184	-0.178	-0.192	-0.199
	(0.084)	(0.087)	(0.082)	(0.086)	(0.091)
Portfolio 1 - 5	0.400***	0.373***	0.380***	0.380***	0.368***
	(0.144)	(0.125)	(0.117)	(0.125)	(0.129)

Table 4: Abnormal returns to portfolios sorted on TAV and size, 3x2

This table reports average monthly excess returns for portfolios sorted by firm exposure to differences in the standard deviation of temperature anomalies, abnormal temperature variability (TAV) and size. Each month t, U.S. states are assigned to terciles based on the cross-sectional distribution of TAV. Within each TAV tercile, firms are further split into two groups by total assets measured at the end of the prior quarter. Portfolio returns are calculated as the value-weighted excess returns of firms headquartered in each group, with portfolios rebalanced monthly. Panel A shows results for smaller firms; Panel B shows results for larger firms. Portfolio 1 contains firms operating in states with the lowest TAV values (low variability), while Portfolios 3 contains firms in states with the highest TAV (high variability). We report the alphas of each portfolio after controlling for combinations of the Fama-French 3, liquidity, betting against beta, momentum, and the Fama-French 5 factors. Differences such as "Portfolio 1–3" report the return spread between firms in the lowest and highest TAV terciles, conditional on firm size. To control for operational dispersion, we select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. The sample period is from January 1993 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 12 lags.

Panel A: Small firms

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.078	0.138	0.158	0.191	0.257**
	(0.187)	(0.126)	(0.127)	(0.137)	(0.113)
Portfolio 2	-0.374	-0.317	-0.294	-0.339	-0.268
	(0.190)	(0.120)	(0.117)	(0.136)	(0.145)
Portfolio 3	-0.398	-0.350	-0.339	-0.391	-0.233
	(0.181)	(0.125)	(0.125)	(0.133)	(0.134)
Portfolio 1 - 3	0.476***	0.489***	0.498***	0.582***	0.490***
	(0.169)	(0.179)	(0.180)	(0.189)	(0.160)

Panel B: Large firms

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.040	-0.008	0.001	-0.038	-0.039
	(0.096)	(0.075)	(0.074)	(0.080)	(0.070)
Portfolio 2	-0.180	-0.228	-0.240	-0.377	-0.360
	(0.107)	(0.103)	(0.101)	(0.105)	(0.116)
Portfolio 3	-0.322	-0.348	-0.351	-0.378	-0.355
	(0.071)	(0.073)	(0.071)	(0.072)	(0.079)
Portfolio 1 - 3	0.361***	0.339***	0.351***	0.341***	0.317***
	(0.117)	(0.104)	(0.102)	(0.113)	(0.111)

Table 5: Fama Macbeth Return Regressions

This table reports Fama-MacBeth regression coefficients from monthly cross-sectional regressions of individual stock excess returns on exposure to differences in the standard deviation of temperature anomalies, abnormal temperature variability (TAV). All regressions control for leverage, log total assets, log book-to-market, Tobin's Q, return on assets, and log of property, plant, and equipment over total assets, measured at the quarterly frequency. Additional controls include the Fama-French three factors, one-month lagged returns, and innovations in the Wall Street Journal news index (Engle et al., 2020). We also include deviations in average temperature, precipitation, and wildfire risk. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. The sample period is from January 1993 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 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
TAV	-0.043***	-0.041***	-0.043***	-0.041***	-0.028**	-0.034***	-0.041***
	(-3.220)	(-3.340)	(-3.889)	(-3.923)	(-2.284)	(-2.880)	(-3.662)
TA							-0.021
							(-0.666)
Precipitation							0.023
							(1.213)
Burning							-0.056
							(-0.838)
WSJ						0.000**	
						(2.412)	
Return, Lag 1					0.010***		
					(3.738)		
Leverage	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	0.000
	(-1.143)	(-0.964)	(-0.983)	(-0.543)	(0.809)	(-0.180)	(0.168)
Total Assets	-0.001***	-0.001**	-0.001	-0.001	-0.001	-0.001	-0.002
	(-2.813)	(-2.242)	(-1.462)	(-0.617)	(-0.540)	(-0.528)	(-1.511)
Bk to Mkt	0.000	0.001	0.001*	0.002	0.000	0.001	0.001
	(0.292)	(1.347)	(1.768)	(1.316)	(0.211)	(1.099)	(0.857)
Tobins Q	-0.000**	-0.001***	-0.000**	-0.000	-0.000	-0.000	-0.001
	(-2.507)	(-2.631)	(-2.343)	(-0.755)	(-0.779)	(-0.391)	(-1.145)
PPE/Assets	-0.000	-0.001*	-0.001**	-0.000	-0.000	-0.000	0.000
	(-0.300)	(-1.892)	(-2.160)	(-0.460)	(-0.014)	(-0.213)	(0.408)
ROA	-0.061**	-0.060**	-0.055	-0.031	-0.040*	-0.038	-0.035
	(-2.377)	(-2.289)	(-1.600)	(-1.047)	(-1.678)	(-1.493)	(-1.326)
Unrate, yoy	0.001	0.000	0.000	0.002	0.003	0.003	0.003
	(0.692)	(0.305)	(0.335)	(0.685)	(0.853)	(0.741)	(0.871)
HPI, yoy	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000*
	(-0.008)	(-0.523)	(-0.287)	(-1.215)	(-1.262)	(-0.732)	(-1.835)
Income, yoy	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-0.687)	(-0.247)	(-0.162)	(-0.229)	(-0.345)	(-0.661)	(-0.384)
Mkt		0.143	0.176	0.212	0.159	0.225	0.214
		(0.640)	(0.839)	(0.958)	(0.708)	(0.941)	(0.986)
SMB			0.043	-0.003	-0.049	0.010	-0.021
			(0.388)	(-0.021)	(-0.408)	(0.077)	(-0.180)
HML			0.069	0.068	0.011	0.088	0.054
			(0.487)	(0.440)	(0.069)	(0.537)	(0.353)
Industry FE	No	No	No	Yes	Yes	Yes	Yes
ADJ R Squared	0.011	0.040	0.073	0.078	0.079	0.087	0.083
Observations	918834	918130	916413	897633	869564	835093	890820

Table 6: Temperature exposure and efficiency

This table presents the results of regressing quarterly revenue, scaled by total assets from the prior quarter, on the quarterly difference in the standard deviation of temperature anomalies—abnormal temperature variability (TAV). All regressions control for leverage, log total assets, log book-to-market, Tobin's Q, return on assets, and log of property, plant, and equipment over total assets, all from the previous quarter. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. All dependent and independent variables, except for TAV, are winsorized at 1%. 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.

	(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	-0.19***	-0.29***	0.05	-0.33	0.08	0.51***	-0.17	-0.29*	-0.11***	-0.56***	-0.12	-0.56***	-0.04	0.06	0.28**
	(-2.77)	(-4.16)	(0.24)	(-1.10)	(0.35)	(6.36)	(-1.52)	(-2.01)	(-4.33)	(-3.56)	(-1.03)	(-5.27)	(-0.53)	(0.56)	(2.49)
L.Total Assets	-12.30***	-12.98***	-13.68***	-8.92***	-17.84***	-6.10***	-12.57***	-15.60***	-6.66***	-14.01***	-14.86***	-16.74***	-9.54***	-14.95***	-5.69***
	(-26.84)	(-28.53)	(-7.00)	(-5.35)	(-4.73)	(-10.74)	(-16.75)	(-10.05)	(-10.39)	(-6.81)	(-19.26)	(-10.66)	(-5.71)	(-7.76)	(-4.79)
L.Bk to Mkt	-1.88***	-2.03***	-2.41	-2.59***	-3.14***	-1.74***	-1.29***	-2.66***	0.09	-2.80***	-1.27***	-3.40***	-0.54**	-0.90*	-4.89***
	(-11.98)	(-10.56)	(-1.58)	(-4.42)	(-3.35)	(-7.72)	(-3.83)	(-6.31)	(1.37)	(-2.75)	(-5.43)	(-6.36)	(-2.47)	(-1.76)	(-3.25)
L.ROA	-0.00**	0.00	-0.01	0.00	0.00	0.00***	0.00	0.00	-0.01*	-0.01	-0.00	-0.04***	0.01*	-0.00	-0.01**
	(-2.60)	(0.50)	(-1.42)	(0.34)	(0.14)	(3.94)	(1.34)	(0.62)	(-1.77)	(-1.63)	(-0.40)	(-9.42)	(1.86)	(-0.55)	(-2.20)
L.Tobins Q	-0.05	-0.26***	0.26	0.71	-1.19	0.86***	-0.00	0.02	1.41***	0.84	0.05	-0.92**	0.11	0.77*	-0.16
	(-1.05)	(-4.03)	(0.35)	(1.05)	(-1.53)	(5.24)	(-0.00)	(0.05)	(6.62)	(1.49)	(0.42)	(-2.46)	(0.44)	(1.69)	(-0.05)
L.PPE/Assets	0.99***	2.38***	0.25	2.25***	1.57	1.27**	0.83***	-0.60	1.37***	-0.08	1.40**	-2.20**	2.13**	2.53**	-12.53***
	(3.83)	(8.79)	(0.15)	(2.75)	(1.03)	(2.45)	(3.02)	(-0.45)	(8.78)	(-0.05)	(2.59)	(-2.03)	(2.25)	(2.54)	(-4.01)
L.Leverage	1.42	-2.21*	9.11	-0.88	-1.02	-1.37	-1.76	4.27	1.00	22.09***	-1.05	2.84	2.24	-9.10**	48.49***
	(0.99)	(-1.81)	(0.84)	(-0.25)	(-0.30)	(-0.90)	(-1.39)	(1.13)	(0.86)	(4.00)	(-0.60)	(0.77)	(0.75)	(-2.28)	(3.22)
Unrate, yoy	-1.61***	-1.84***	-2.36**	-1.61*	-3.56***	-3.56***	-0.77*	-2.58***	-0.23**	-2.15***	-2.04***	-2.09***	0.17	-3.60***	-1.62**
	(-5.64)	(-3.53)	(-2.67)	(-1.94)	(-3.58)	(-3.26)	(-1.82)	(-4.16)	(-2.11)	(-3.50)	(-5.00)	(-3.03)	(0.43)	(-7.06)	(-2.61)
HPI, yoy	0.79	0.70	-11.20**	9.09**	-9.11	1.19	-0.88	2.86	1.51***	-0.74	1.30	1.70	2.15	4.84	1.77
	(0.99)	(0.62)	(-2.05)	(2.59)	(-0.91)	(0.38)	(-0.33)	(0.53)	(3.87)	(-0.22)	(0.82)	(0.93)	(0.37)	(1.29)	(0.66)
Income, yoy	5.41	10.32*	15.83*	7.84	16.37***	34.44***	-0.69	9.55	0.48	2.06	5.51***	6.59	4.28	7.63**	3.78*
	(1.58)	(1.87)	(1.94)	(1.24)	(2.84)	(14.92)	(-0.32)	(1.42)	(1.26)	(1.13)	(2.71)	(1.64)	(1.04)	(2.17)	(1.88)
FirmYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Squared	0.94	0.90	0.87	0.90	0.87	0.94	0.93	0.86	0.97	0.81	0.94	0.87	0.95	0.95	0.79
Observations	286604	47183	4583	10246	7077	8380	26119	22002	64493	15634	23822	30780	6008	9501	10776

Table 7: Temperature exposure and profitability

This table presents the results of regressing quarterly income before extraordinary items, scaled by total assets from the prior quarter, on the quarterly difference in the standard deviation of temperature anomalies—abnormal temperature variability (TAV). All regressions control for leverage, log total assets, log book-to-market, Tobin's Q, return on assets, and log of property, plant, and equipment over total assets, all from the previous quarter. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. All dependent and independent variables, except for TAV, are winsorized at 1%. 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.

	(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	-0.06**	-0.15*	-0.10	-0.14**	-0.01	0.29***	-0.02	-0.09	-0.03**	-0.19***	0.01	-0.08**	-0.08	-0.08	0.02
	(-2.20)	(-1.77)	(-1.66)	(-2.64)	(-0.23)	(8.29)	(-0.41)	(-1.67)	(-2.47)	(-4.48)	(0.21)	(-2.03)	(-0.78)	(-1.43)	(0.72)
L.Total Assets	-0.07	-0.19	0.13	-0.25	-0.16	-1.90***	1.86***	-0.62	-0.33***	-1.05**	-0.57	-0.12	0.20	-0.44	-0.63*
	(-0.37)	(-0.81)	(0.14)	(-0.90)	(-0.27)	(-4.82)	(2.72)	(-1.55)	(-3.09)	(-2.46)	(-1.64)	(-0.52)	(0.51)	(-0.89)	(-1.83)
L.Bk to Mkt	-1.22***	-1.41***	-1.91***	-1.31***	-1.56***	-1.87***	-1.05***	-1.71***	-0.37***	-1.27***	-1.39***	-1.48***	-0.78***	-1.20***	-1.40***
	(-17.19)	(-11.81)	(-4.29)	(-6.15)	(-4.47)	(-14.68)	(-6.10)	(-11.24)	(-4.66)	(-4.65)	(-9.15)	(-13.69)	(-3.91)	(-5.34)	(-5.21)
L.ROA	-0.01***	-0.01***	-0.01***	-0.01***	-0.01**	0.00	-0.01***	-0.01***	-0.01**	-0.01***	-0.01***	-0.01***	-0.00	-0.01***	-0.01
	(-12.49)	(-15.03)	(-3.23)	(-7.15)	(-2.69)	(0.39)	(-2.92)	(-4.84)	(-2.39)	(-5.89)	(-11.33)	(-11.15)	(-1.16)	(-4.73)	(-1.22)
L.Tobins Q	-0.13***	-0.13***	-0.39	-0.01	-0.43*	0.19	-0.21***	-0.29**	0.16	-0.07	-0.15*	-0.33***	-0.16	-0.37**	-0.29
	(-4.65)	(-3.09)	(-1.64)	(-0.05)	(-1.79)	(1.30)	(-3.19)	(-2.64)	(1.51)	(-0.58)	(-1.89)	(-4.33)	(-1.26)	(-2.16)	(-0.54)
L.PPE/Assets	-0.65***	-1.15***	0.42	-0.42	0.59*	-0.89***	-0.58**	-0.70*	0.02	-0.35	-0.56***	-1.10***	-0.66**	-0.54	-1.46***
	(-5.74)	(-7.61)	(0.65)	(-1.18)	(1.78)	(-4.88)	(-2.31)	(-1.91)	(0.23)	(-1.12)	(-3.05)	(-4.13)	(-2.18)	(-0.85)	(-2.90)
L.Leverage	0.17	0.47	-0.52	1.11	0.22	0.15	-2.83***	0.68	0.12	5.15***	0.11	0.93*	-4.25***	-1.79**	10.62***
	(0.46)	(0.77)	(-0.23)	(1.65)	(0.36)	(0.22)	(-3.72)	(0.72)	(0.36)	(4.80)	(0.13)	(1.70)	(-3.32)	(-2.21)	(3.84)
Unrate, yoy	-0.96***	-1.39***	-1.43***	-0.97***	-2.26***	-2.32***	-0.72**	-1.48***	-0.21***	-1.61***	-1.01***	-0.62***	-2.36***	-0.72**	-0.32**
	(-8.61)	(-4.38)	(-3.50)	(-2.74)	(-5.94)	(-6.18)	(-2.18)	(-4.98)	(-3.65)	(-5.89)	(-4.16)	(-3.46)	(-4.38)	(-2.21)	(-2.07)
HPI, yoy	-0.74	-1.82	-2.47	2.96	-1.84	-2.52	-2.71	-2.06	1.39***	-0.26	-0.49	0.66	-0.94	0.72	-0.97
	(-0.82)	(-1.40)	(-0.83)	(1.68)	(-0.86)	(-1.11)	(-1.08)	(-1.50)	(4.16)	(-0.34)	(-0.40)	(0.79)	(-0.25)	(0.48)	(-1.14)
Income, yoy	1.03**	-0.39	3.62	2.60***	1.88	10.96***	-0.26	2.03***	0.44**	0.09	1.51	0.11	4.99	1.49**	0.86***
	(2.05)	(-0.30)	(0.89)	(4.21)	(0.85)	(4.13)	(-0.25)	(2.79)	(2.45)	(0.18)	(1.28)	(0.17)	(1.63)	(2.33)	(3.53)
FirmYear FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Squared	0.65	0.64	0.59	0.52	0.62	0.49	0.77	0.54	0.61	0.47	0.56	0.54	0.65	0.58	0.19
Observations	288369	46165	4556	10218	7025	8299	26003	21860	66095	15443	24014	32241	6026	9656	10768

Table 8: Yale Climate Opinions

This table presents results regressing state-level survey questions on climate risk perceptions—measured as AR(1) residuals for three belief questions from Yale Climate surveys—on abnormal temperature variability (TAV). The raw values measure the percentage of respondents for each state from 2010-2019 answering "Yes" to the following questions: (a) whether they believe climate change is happening; (b) whether they somewhat or strongly agree that they have personally experienced the effects of global warming; and (c) whether they think global warming will harm people in the US a moderate amount or a great deal. Economic controls, other physical risk variables and state or year fixed effects are included. 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.

	(1) Happen	(2) Happen	(3) Happen	(4) Happen	(5) Exp	(6) Exp	(7) Exp	(8) Exp	(9) Harm	(10) Harm	(11) Harm	(12) Harm
TAV	-0.246	-0.228	-0.223	-0.278	1.045***	1.104***	1.200***	1.258***	0.526*	0.644*	0.686*	0.821*
	(0.213)	(0.214)	(0.224)	(0.298)	(0.290)	(0.289)	(0.307)	(0.351)	(0.310)	(0.337)	(0.343)	(0.412)
SVI, Innov		0.063**	0.061*	0.057*		0.091**	0.091*	0.098*		0.083**	0.084**	0.094**
		(0.028)	(0.031)	(0.033)		(0.044)	(0.046)	(0.052)		(0.037)	(0.038)	(0.042)
TA		-0.135	-0.119	-0.202**		-0.185*	-0.208	-0.289**		-0.076	-0.088	-0.121
		(0.083)	(0.092)	(0.098)		(0.108)	(0.124)	(0.139)		(0.114)	(0.125)	(0.142)
Precipitation		-0.420**	-0.415**	-0.281		-0.323*	-0.333*	-0.291		-0.697***	-0.702***	-0.703***
		(0.173)	(0.172)	(0.194)		(0.187)	(0.186)	(0.227)		(0.193)	(0.195)	(0.241)
Burning		-0.036*	-0.040*	-0.011		0.012	0.006	0.024		0.002	-0.001	0.009
		(0.021)	(0.022)	(0.024)		(0.029)	(0.028)	(0.037)		(0.033)	(0.033)	(0.042)
HPI, yoy			-0.857	-1.406			5.318**	7.197*			2.280	2.149
			(2.002)	(2.821)			(2.583)	(3.799)			(1.628)	(2.578)
Income, yoy			1.749	3.044*			1.927	4.908**			1.113	2.290
			(1.294)	(1.773)			(1.509)	(2.272)			(1.045)	(1.529)
Unrate, yoy			-0.367	-0.091			-0.617	-0.416			0.048	0.188
			(1.193)	(1.297)			(1.128)	(1.278)			(1.013)	(1.126)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Adj R Squared	0.768	0.772	0.771	0.754	0.806	0.808	0.809	0.790	0.816	0.822	0.821	0.801
Obs	432	432	432	432	432	432	432	432	432	432	432	432

Table 9: TAV and state-specific climate attention

This table presents results associating the innovations in the Google Search topic "Climate Change" to the quarterly difference in the standard deviation of temperature anomalies—abnormal temperature variability (TAV). The attention index, at the quarterly frequency, is regressed onto TA and TAV with varying fixed effects. Standard errors are clustered at the US state level. T-statistics are reported in parentheses. Statistical significance is calculated at the 1%, 5%, and 10% levels are indicated by ***, **, *, respectively.

	(1)	(2)	(3)	(4)	(5)
TAV	1.602***	1.825***	1.779***	0.796***	2.210***
	(4.59)	(5.54)	(5.28)	(2.90)	(4.31)
HPI, yoy		3.478	3.591	5.858*	11.464
		(1.05)	(1.06)	(1.71)	(1.40)
Income, yoy		7.140	7.233	6.913	7.412
		(1.63)	(1.63)	(1.67)	(1.13)
Unrate, yoy		9.079***	8.924***	9.017***	-10.072***
		(12.95)	(12.80)	(12.79)	(-6.50)
TA			-0.239**	-0.315***	-0.242**
			(-2.60)	(-4.04)	(-2.27)
Precipitation			0.004	0.363	0.166
			(0.01)	(1.38)	(0.42)
Burning			0.007	0.157***	-0.197**
			(0.13)	(3.35)	(-2.29)
StateQuarter FE	No	No	No	Yes	No
StateYear FE	No	No	No	No	Yes
R Squared	0.003	0.030	0.031	0.412	0.245
Observations	3024	3024	3024	3024	3024

Table 10: Associating TAV with the Wall Street Journal News Index

This table presents results associating the innovations in the national Wall Street Journal news index developed by Engle et al. (2020) to the quarterly difference in the standard deviation of temperature anomalies—abnormal temperature variability (TAV). The attention index at the quarterly frequency and multiplied by 1,000, is regressed onto 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.

	(1)	(2)	(3)	(4)	(5)
TAV	0.801*	0.843*	0.767*	0.771*	0.657
	(1.762)	(1.778)	(1.716)	(1.686)	(1.438)
TA			-0.132	-0.131	-0.171
			(-1.038)	(-1.048)	(-1.337)
Precipitation				0.025	0.278
				(0.073)	(0.751)
Burning					0.070
					(1.385)
Quarter FE	None	Yes	Yes	Yes	Yes
Adj R Squared	0.029	0.083	0.087	0.077	0.079
Observations	98	98	98	98	98

Table 11: The impact TAV on the attention paid by earnings call participants to climate risk

This table presents results associating the physical climate exposure attention index developed by Sautner et al. (2023) to the yearly difference in the standard deviation of temperature anomalies—abnormal temperature variability (TAV). The yearly innovations in the attention index is regressed onto 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 5% of the time over all other states in their 10Ks and those with more than 73% of revenues from the US. The sample period is from 1993 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.

	(1)	(2)	(3)	(4)
TAV	0.149**	0.211***	0.215***	0.138**
	(2.467)	(3.257)	(3.342)	(2.208)
L.Total Assets		-0.005	-0.007	-0.013
		(-0.327)	(-0.466)	(-0.884)
L.Bk to Mkt		0.082*	0.084**	0.068*
		(2.009)	(2.046)	(1.769)
L.ROA		-0.002***	-0.001***	-0.001***
		(-3.751)	(-3.653)	(-3.251)
L.Tobins Q		-0.007	-0.008	-0.011
		(-0.372)	(-0.393)	(-0.512)
L.PPE/Assets		0.089***	0.092***	0.084***
		(3.542)	(3.589)	(3.156)
L.Leverage		-0.516***	-0.524***	-0.538***
		(-2.821)	(-2.895)	(-2.975)
TA			-0.012	0.044*
			(-0.401)	(1.900)
Precipitation			-0.074	-0.007
			(-1.421)	(-0.133)
Burning			-0.022	-0.016
			(-1.573)	(-1.101)
WSJ Innov				127.832***
				(7.340)
Industry FE	No	Yes	Yes	Yes
R Squared	0.332	0.366	0.366	0.358
Obs	30376	25867	25867	22998

Table 12: Temperature exposure and analyst earnings surprises

This table presents the results of regressing quarterly earnings-per-share surprises on 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 5% of the time relative to all states mentioned in their 10-K filings and firms with more than 73% of revenues within the US. The quarterly sample period is from 1993 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.

	(1) STDV	(2) STDV	(3) STDV	(4) STDV	(5) STDV	(6) Mean	(7) Mean	(8) Mean	(9) Mean	(10) Mean
TAV	0.045**	0.020**	0.020**	0.005	0.005	-0.074**	-0.076***	-0.076***	-0.045***	-0.051***
	(2.471)	(2.265)	(2.265)	(0.819)	(0.946)	(-2.508)	(-3.806)	(-3.806)	(-2.911)	(-3.309)
L.TAV					-0.005					-0.006
					(-1.161)					(-0.210)
L.Total Assets	0.087***	0.144***	0.144***	0.071**	0.071**	0.152***	0.189***	0.189***	0.726***	0.726***
	(10.573)	(11.801)	(11.801)	(2.318)	(2.342)	(6.883)	(4.594)	(4.594)	(3.962)	(3.914)
L.Bk to Mkt	0.201***	0.139***	0.139***	0.081***	0.081***	-0.147**	-0.847***	-0.847***	-1.207***	-1.207***
	(10.194)	(7.886)	(7.886)	(5.013)	(5.020)	(-2.587)	(-8.017)	(-8.017)	(-4.233)	(-4.243)
L.ROA	-0.005***	-0.002***	-0.002***	-0.001***	-0.001***	0.038***	0.021***	0.021***	0.004***	0.004***
	(-13.785)	(-12.691)	(-12.691)	(-7.319)	(-7.380)	(37.408)	(22.956)	(22.956)	(5.102)	(5.097)
L.Tobins Q	0.028***	0.016*	0.016*	0.006	0.006	-0.168***	-0.168***	-0.168***	-0.155***	-0.155***
	(3.316)	(1.860)	(1.860)	(0.880)	(0.870)	(-3.120)	(-3.447)	(-3.447)	(-3.618)	(-3.616)
L.PPE/Assets	0.085***	0.070***	0.070***	0.034	0.033	-0.110***	-0.248***	-0.248***	-0.370***	-0.368***
	(5.238)	(4.994)	(4.994)	(1.609)	(1.571)	(-8.340)	(-4.637)	(-4.637)	(-5.286)	(-5.294)
L.Leverage	0.513***	0.446***	0.446***	0.369***	0.367***	0.578***	-0.857***	-0.857***	-0.153	-0.145
	(8.165)	(8.436)	(8.436)	(4.393)	(4.394)	(4.921)	(-2.973)	(-2.973)	(-0.286)	(-0.270)
HPI, yoy	-1.559***	-1.262***	-1.262***	-0.245*	-0.239*	-0.246	-0.324	-0.324	-0.111	-0.103
	(-8.556)	(-8.020)	(-8.020)	(-1.843)	(-1.829)	(-0.499)	(-0.903)	(-0.903)	(-0.121)	(-0.115)
Income, yoy	0.023	0.054*	0.054*	0.107	0.099	0.595*	0.548**	0.548**	1.821***	1.841***
	(0.200)	(1.739)	(1.739)	(0.989)	(0.904)	(1.774)	(2.141)	(2.141)	(4.501)	(4.231)
Unrate, yoy	-0.215***	-0.039	-0.039	0.158***	0.153***	-0.829***	-0.460***	-0.460***	-0.282**	-0.261**
	(-4.211)	(-1.307)	(-1.307)	(6.213)	(5.846)	(-6.817)	(-5.692)	(-5.692)	(-2.469)	(-2.283)
Analysts, Number		0.016***	0.016***	0.015***	0.015***		-0.008*	-0.008*	-0.002	-0.001
		(11.777)	(11.777)	(9.070)	(9.019)		(-1.755)	(-1.755)	(-0.490)	(-0.447)
TA				-0.002					0.015**	
				(-1.197)					(2.366)	
Precipitation				0.002					0.002	
				(0.431)					(0.188)	
Burning				0.000					0.002	
				(0.115)					(1.151)	
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes	No	No
FirmxYear FE	No	No	No	No	Yes	No	No	No	Yes	Yes
Adj R Squared	0.117	0.457	0.457	0.625	0.625	0.180	0.321	0.321	0.555	0.555
Obs	159110	155115	155115	149269	149269	199114	184944	184944	178672	178672

Table 13: Fama Macbeth Volatility Regressions

This table reports Fama-MacBeth regression coefficients from monthly cross-sectional regressions of individual stock idiosyncratic return volatility on TAV. All regressions control for leverage, log total assets, log book-to-market, Tobin's Q, return on assets, and log of property, plant, and equipment over total assets, measured at the quarterly frequency. Additional controls include the Fama-French three factors, one-month lagged returns, and innovations in the Wall Street Journal news index (Engle et al., 2020). We also include deviations in average temperature, precipitation, and wildfire risk. The sample period is from January 1993 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 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TAV	0.136***	0.066**	0.142***	0.164***	0.219***	0.136***	0.104**	0.092**
	(3.314)	(2.090)	(5.072)	(3.967)	(5.310)	(3.957)	(2.450)	(2.254)
TAV, lag 1								-0.045
								(-1.006)
TA					0.015			
					(0.142)			
Precipitation					-0.061			
					(-1.092)			
Burning					-0.298			
					(-1.359)			
Analyst Dispersion							0.042***	0.034***
							(3.752)	(2.592)
WSJ						0.001***		
						(3.684)		
Return, lag 1				0.133***	0.157***	0.147***	0.152***	0.157***
				(12.520)	(16.842)	(14.185)	(12.033)	(13.600)
VIX, changes			-0.278***	-0.243***	-0.271***	-0.273***	-0.157***	-0.158***
			(-10.801)	(-11.097)	(-10.357)	(-11.180)	(-11.333)	(-12.086)
IVOL, lag 1		-0.422***	-0.334***	-0.299***	-0.213***	-0.197***	-0.550***	-0.540***
		(-10.933)	(-8.309)	(-7.933)	(-5.001)	(-4.112)	(-21.495)	(-20.684)
Leverage	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000**	0.000**
	(0.437)	(-0.404)	(-1.617)	(-0.535)	(-1.039)	(-0.008)	(2.552)	(2.263)
Total Assets	-0.001	-0.001	-0.001*	-0.001*	-0.005*	-0.002	0.005**	0.005**
	(-1.206)	(-1.534)	(-1.752)	(-1.829)	(-1.760)	(-0.414)	(2.431)	(2.016)
Bk to Mkt	-0.002	0.000	0.000	0.001	-0.000	-0.003	-0.005***	-0.006***
	(-0.738)	(0.135)	(0.120)	(0.673)	(-0.079)	(-1.229)	(-3.006)	(-4.280)
Tobins Q	-0.001**	-0.001***	-0.001***	-0.001***	0.001	0.001	0.002***	0.002***
	(-2.244)	(-3.117)	(-2.705)	(-2.859)	(0.657)	(1.307)	(5.392)	(5.764)
PPE/Assets	-0.002**	-0.002*	-0.003***	-0.002	-0.003	-0.003	-0.004***	-0.004**
	(-2.215)	(-1.806)	(-2.819)	(-1.617)	(-1.350)	(-1.549)	(-3.242)	(-2.319)
ROA	0.200**	0.180***	0.162**	0.201***	0.567***	0.363***	0.236***	0.295***
	(2.426)	(2.817)	(2.588)	(3.481)	(7.371)	(5.789)	(4.021)	(4.336)
Unrate, yoy	-0.003	0.001	0.001	0.000	0.002	0.001	0.005	0.007
	(-1.361)	(0.506)	(0.570)	(0.376)	(0.321)	(0.301)	(1.483)	(1.426)
HPI, yoy	-0.000	-0.001	0.000	-0.000	-0.001	-0.001	0.001**	0.000
	(-0.297)	(-0.808)	(0.019)	(-0.518)	(-0.730)	(-0.923)	(2.450)	(0.870)
Income, yoy	-0.004***	-0.002***	-0.002***	-0.002***	-0.005***	-0.005**	-0.004***	-0.004***
	(-3.214)	(-3.216)	(-3.334)	(-2.887)	(-3.074)	(-2.590)	(-3.183)	(-2.919)
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
ADJ R Squared	0.013	0.035	0.049	0.055	0.080	0.079	0.120	0.122
Observations	904631	881881	880849	868420	841566	789038	437769	436481

Table 14: Expenditure categories and their corresponding FMLI variables

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.

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

Table 15: Control variables for consumer expenditure regressions

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

Controls	FMLI Name	Categorical or Continuous
Age	age_ref	Continuous
Number of rooms	roomsq	
Family income before taxes	fincbtax	
Cars	num_auto	
Family size	fam_size	
Number of earners	no_earnr	
Marital status	marital1	Categorical
Education	educ_ref	
Race	ref_race	
Urban or rural	bls_urbn	
Housing tenure	cutenure	

Table 16: Household expenditure sensitivity to temperature

This table presents regressions relating TAV to household expenditures, as obtained from the US Consumer Expenditure Survey from 1994 to 2019. The dependent variables are the log-transformed expenditure variables of each consumer unit (household) and are described in detail in Table 14. 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 by quarter and state by year 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.

	(1) Tot Exp	(2) Non-Durbl	(3) Durbl	(4) Elect	(5) Hlth Care	(6) Enter	(7) Appar	(8) Tot Exp	(9) Non-Durbl	(10) Durbl	(11) Elect	(12) Hlth Care	(13) Enter	(14) Appar
TAV	-0.01***	-0.01**	-0.02*	0.01**	0.00	-0.01	-0.02**	-0.01***	-0.01**	-0.02*	0.01**	0.00	-0.01	-0.02**
	(-3.11)	(-2.45)	(-1.93)	(2.21)	(0.69)	(-1.10)	(-2.15)	(-3.30)	(-2.61)	(-1.84)	(2.08)	(0.72)	(-1.18)	(-2.18)
TA								-0.00	-0.00	0.00	-0.01***	0.00	-0.00	-0.00
								(-1.31)	(-1.15)	(0.78)	(-3.27)	(0.46)	(-1.26)	(-0.19)
Precipitation								-0.00	-0.00	-0.01	-0.00	0.00	-0.00	0.00
								(-0.36)	(-0.34)	(-1.04)	(-0.72)	(0.49)	(-0.96)	(0.33)
Burning								0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
								(1.09)	(-0.32)	(-0.88)	(-0.52)	(-0.78)	(-1.56)	(0.70)
CPI, yoy	0.01**	0.00	-0.00	0.05***	0.01	-0.00	-0.00	0.01**	0.00	-0.00	0.05***	0.01	-0.00	-0.00
	(2.23)	(0.27)	(-0.03)	(7.65)	(0.84)	(-0.47)	(-0.04)	(2.19)	(0.28)	(-0.00)	(7.60)	(0.93)	(-0.40)	(-0.06)
HPI, yoy	0.00	-0.05	0.66**	0.08	-0.05	0.21	0.25	0.00	-0.05	0.67**	0.07	-0.05	0.20	0.25
	(0.07)	(-0.77)	(2.08)	(0.80)	(-0.36)	(1.68)	(1.45)	(0.04)	(-0.79)	(2.09)	(0.66)	(-0.33)	(1.64)	(1.45)
Income, yoy	-0.02	0.05	-0.30	-0.12	-0.03	0.20*	-0.07	-0.02	0.05	-0.30	-0.11	-0.02	0.21*	-0.07
	(-0.44)	(1.08)	(-1.22)	(-1.26)	(-0.15)	(1.70)	(-0.52)	(-0.44)	(1.11)	(-1.23)	(-1.23)	(-0.14)	(1.69)	(-0.52)
Unrate, yoy	0.00	-0.02	-0.05	0.01	0.04	0.05**	-0.00	0.00	-0.02	-0.05	0.02	0.04	0.05**	-0.00
	(0.24)	(-1.48)	(-1.03)	(0.57)	(1.46)	(2.06)	(-0.05)	(0.27)	(-1.36)	(-1.10)	(0.93)	(1.54)	(2.20)	(-0.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YearQuarter	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADJ R Squared	0.58	0.47	0.08	0.39	0.24	0.24	0.18	0.58	0.47	0.08	0.39	0.24	0.24	0.18
Observations	406154	405615	246619	381825	332172	368106	327585	406154	405615	246619	381825	332172	368106	327585

Table 17: Minutes worked on the prior day

This table presents results associating the minutes worked on the previous day to TAV and TA calculated over 15 days. 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.

	(1) 2003-2019	(2) 2003-2019	(3) 2007-2014	(4) 2003-2019	(5) 2003-2019	(6) 2007-2014
TAV	-0.154	-0.764	-0.744	-0.237	-0.928	-0.744
	(0.532)	(0.734)	(1.093)	(0.534)	(0.735)	(1.081)
Highrisk=1 × TAV	-2.907**	-2.742**	-3.978**	-2.964**	-2.805**	-4.010**
	(1.269)	(1.275)	(1.721)	(1.308)	(1.317)	(1.772)
TA				-0.514**	-0.715***	-0.122
				(0.230)	(0.256)	(0.359)
Highrisk=1 × TA				-0.248	-0.284	-0.086
				(0.528)	(0.520)	(0.755)
Precipitation				-0.478	-0.303	0.624
				(0.433)	(0.507)	(0.621)
Burning				-0.045	0.021	0.316*
				(0.132)	(0.132)	(0.188)
Constant	-11.341**	-10.145**	-2.552	-11.150**	-9.951**	-3.111
	(4.849)	(4.956)	(8.107)	(4.799)	(4.917)	(8.073)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
IndxYear	Yes	Yes	Yes	Yes	Yes	Yes
StatexYrxQ	No	Yes	Yes	No	Yes	Yes
Adj R Squared	0.345	0.346	0.338	0.345	0.346	0.338
Observations	130058	130046	60704	130058	130046	60704

A Appendix

A.1 Robustness

A.1.1 Placebo tests

To address the possibility of spurious correlations in our portfolio sorts, we implement two placebo tests that preserve the structure of the temperature data. First, we randomly shuffle the TAV observations across states within each month (cross-sectional), and second, we shuffle TAV within each state over time (time series). Using these randomized allocations, we repeat our long-short portfolio analysis, sorting into quartile or quintile portfolios and regressing the resulting long-short returns on the Fama-French 3 factor model, to extract the estimated alpha.

We repeat this procedure 5,000 times and report the distribution of estimated alphas for quartile sorts in panels (a) and (b), and for quintile sorts in panels (c) and (d) of Figure 5. The placebo distributions are approximately normal, with the actual coefficients from our main specification—0.362 for quartile sorts and 0.373 for quintile sorts—shown as vertical dashed lines. Fewer than 0.4% of placebo estimates exceed the realized coefficient, indicating our sorting captures the effect of TAV on equity returns rather than spurious correlations tied to state or economic structure. Moreover, the normally distributed coefficients suggest that the state-level sorting procedure does not inherently favor states with more public firms, supporting the robustness of our findings.

A.1.2 Other physical risks and portfolio sorts

As an additional robustness check for our portfolio sorting exercise, we repeat the analysis using the other physical risk variables as the main sorting criteria. This approach is natural, as climate change can drive a range of weather extremes beyond temperature variability, including precipitation extremes Allan and Soden (2008). Specifically, we use average deviations in temperature anomalies, precipitation, and the wildfire index as alternative sorting

variables. The sorting methodology follows the procedure described in Section 3.2.

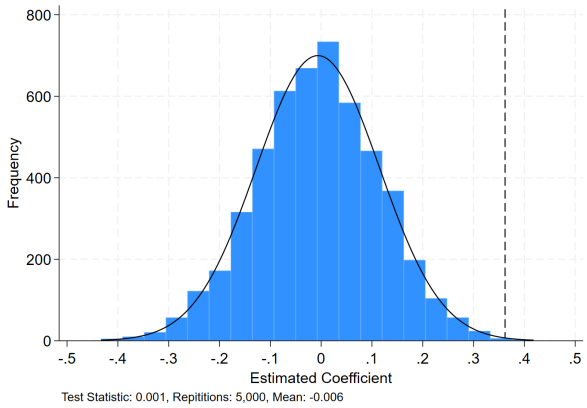
Tables 19, 20, and 21 report the results of quartile and quintile portfolio sorts using TA, average deviations in precipitation, and average deviations in wildfire index, respectively. The final rows of each table show no significant difference in excess returns for the long-short portfolios based on these variables, indicating that firm performance does not systematically vary with these criteria. The absence of significant effects for average temperature deviations aligns with the findings of Addoum et al. (2020) and Addoum et al. (2023), who also find no immediate market response to extremely hot temperatures.

A.2 Figures

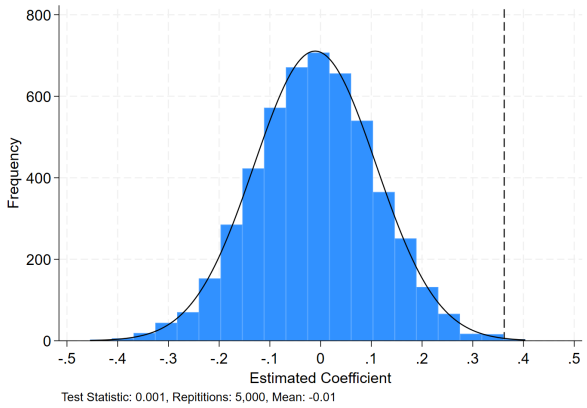
Figure 5: Placebo tests: alpha coefficients after controlling for FF3 factors

This figure presents the Fama-French 3-factor adjusted alphas from a long-short strategy that sorts the 48 U.S. states, along with the firms headquartered in those states, into quartiles or quintiles. While preserving the structure of the data, we randomly assign state values of TAV either in the cross-section (panels (a) and (c)) or in the time series (panels (b) and (d)). Firms in each group are value-weighted to construct portfolio returns, which are rebalanced monthly. We compute factor-adjusted returns by subtracting the return of the highest TAV quartile or quintile portfolio from the lowest and regress the resulting portfolio returns on the FF 3-factor model. This randomization is repeated 5,000 times—either cross-sectionally or through time—to generate the distribution of alphas shown. The vertical dashed line represents the actual coefficient estimate from our main specification. The test statistic is the fraction of coefficients from these randomized regressions that exceed the actual estimate.

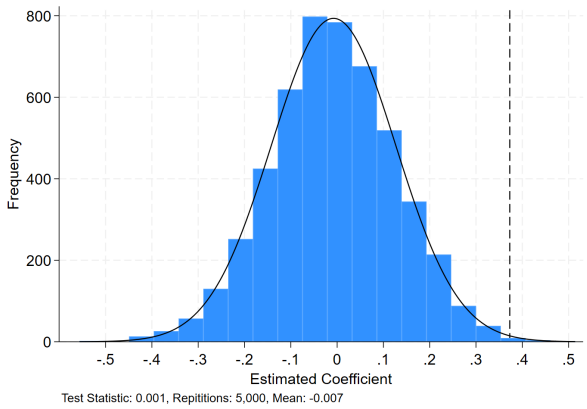
(a) Quartile sort: cross-sectional shuffle



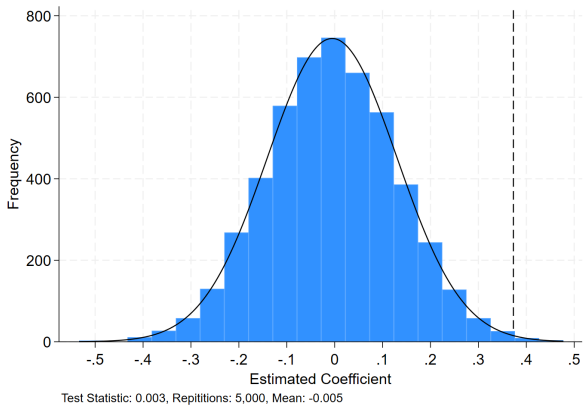
(b) Quartile sort: time-series shuffle



(c) Quintile sort: cross-sectional shuffle



(d) Quintile sort: time-series shuffle



A.3 Tables

Table 18: Definition of variables used.

Weather and Climate Variables	
Variable	Definition
TAV	The variable measures the standard deviation of temperature anomalies for a given month, quarter, or year in a U.S. state, minus the 25-year historical standard deviation for the same period and state. Source: NCEI (NOAA).
TA	The monthly, quarterly, or yearly average temperature anomaly in a U.S. state minus the 25-year historical average for the same period and state. Source: NCEI (NOAA).
Precipitation	The monthly, quarterly, or yearly average of precipitation anomalies in a U.S. state minus the 13-year historical average for the same period and state. Source: Gridded Surface Meteorological (gridMET).
Burning	The burning index is a number used by NOAA to describe the potential amount of effort needed to contain a single fire in a particular fuel type. The monthly, quarterly, or yearly average of the burning index in a U.S. state minus the 13-year historical average for the same period and state. Source: Gridded Surface Meteorological (gridMET).
Compustat and Other Firm Level Variables	
Variable	Definition
Leverage	Short-term debt (DLCQ) plus long-term debt (DLTTQ) divided by total assets (ATQ).
Income/L1.Assets	Income before extraordinary items (IBQ) divided by one-quarter lagged total assets (ATQ)
Revenues/L1.Assets	Revenues (REVTQ) divided by one-quarter lagged total assets (ATQ). Revenues replaced by sales (SALEQ) if missing.
Total Assets, ln	Natural log of total assets (ATQ).
Bk to Mkt, ln	Natural log of book to market equity. (SEQQ+ TXDITCQ-PSTKQ)/(PRCCQ*CSHOQ)
ROA	Return on assets. (IBQ/(ATQ))*1000
Tobin's Q	Tobin's Q. (ATQ +(CSHOQ*PRCCQ) - CEQQ)/ATQ.
PPE/Assets, ln	Planet, property, and equipment divided by total assets. ln(PPENTQ/ATQ).
Forecast Dispersion, ln	The natural log of the standard deviation of analyst estimates (SURPSTDEV). Source: I/B/E/S.
Mean Surprise/L1.Price, %	Average difference between reported earnings and the mean analyst estimate (SURPMEAN) divided by the prior month's stock price. Source: I/B/E/S.
CC Exposure	Climate change exposure index. Source: Sautner et al., (2023).
US Revenue Concentration	Compustat segments data to measure the average percentage of sales of the firm in the US versus all countries across all observations.
Near Headquarters	We parse 10-K filings of Russell 3000 firms to count each mention of a U.S. state in sections 1A, 2, 6, and 7. The headquarter citation ratio is the number of mentions of the firm's headquarter state divided by total state mentions, averaged across filing. The same methodology as Garcia and Norli (2012).
Returns, %	Returns adjusted for mergers. Source: CRSP.
Idiosyncratic Volatility	Standard deviation of residual returns from regressions of daily returns (RET) on the Fama and French (1993) three factors computed over a month. Source: CRSP and Kenneth French's Data Library.

Variable definitions continued.

Panel (C): State Variables	
Variable	Definition
Yale Exposure, Innov	Survey data on the percentage of respondents in a US state who beliefe whether they have personally experienced the effects of global warming. Source: Yale Climate Opinion.
Yale Happening, Innov	Survey data on the percentage of respondents in the US who believe climate change is happening in a US state. Source: Yale Climate Opinion.
Yale Harm, Innov	Survey data on the percentage of respondents in a US state who think global warming will harm people in the US. Source: Yale Climate Opinion.
Population	Yearly population (POP) for each US state. Source: Federal Reserve Bank Of St. Louis.
HPI, yoy	The year-over-year growth rate of the All-Transactions House Price Index (STHPI) for each US state. Source: Federal Reserve Bank Of St. Louis.
Income, yoy	The year-over-year growth rate of the Total Personal Income (OTOT) for each US state. Source: Federal Reserve Bank Of St. Louis.
Unrate, yoy	The year-over-year growth rate of the Unemployment Rate (UR) for each US state. Source: Federal Reserve Bank Of St. Louis.
Google SVI, Innov	State-level Google search volume index for the topic "Climate Change" ('/m/0d063v'). The innovations are the residuals from AR(1) models at the state level.
Time Series Data	
Mkt-RF	Market factor. Source: Ken French's data store.
SMB	Small-minus-big factor. Source: Ken French's data store.
HML	High-minus-low factor. Source: Ken French's data store.
RMW	Robust-minus-weak factor. Source: Ken French's data store.
CMA	Conservative-minus-aggressive factor. Source: Ken French's data store.
BAB	betting against beta factor. Source: AQR capital.
MOM	Momentum factor. Source: Ken French's data store.
LIQ	Liquidity factor. Source: Pastor-Stambaugh liquidity series.
RF	Risk free rate: Source: Ken French's data store.
VIX	CBOE volatility index. Source: CBOE.
CPI	Consumer price index. Source: Federal Reserve Bank Of St. Louis.

Variable definitions continued.

Bureau of Labor Statistics: Public Use Microdata	
Total Expenditure, ln	Natural log of total expenditure (totexp).
Non Durables, ln	Natural log of expenditures on non-durables. (fdhome + fdxmap + alcbev + gasmo + pubtra + persca + tobacc + misc + apparel + entert + read)
Durables, ln	Natural log of expenditures on durables. (houseq + cartkn + cartku)
Electricity, ln	Natural log of expenditures on electricity. (houseq + cartkn + cartku)
Health Care, ln	Natural log of expenditures ealth health-care (health).
Entertainment, ln	Natural log of expenditures on entertainment (entert).
Aparrel, ln	Natural log of expenditures on aparrel. (menboys + womgrl + chldrn + footwr + othapl)
Family Income, before tax	Family income before tax. (fincbtax)
Age	Age of respondent.
Rooms	Number of rooms.
Family Size	Family size.
Earners	Number of earners in the family.
Sex	Sex of respondent.
Urban	Household is urban.
Marital Status	Marital status of respondent.
Education	Education of respondent.
Race	Race of respondent.
Housing Tenure	How long they have been in the house for.
American Time Use Survey	
Age	Age of respondent.
Children	Number of children.
White	Indicator representing whether the respondent is white.
College Degree	Indicator representing whether the respondent has a college degree or higher.
High School Grad	Indicator representing whether the respondent is a high school graduate.
Cohabitating	Indicator representing whether the respondent is cohabitating.
Full-Time Emp	Indicator representing whether the respondent is full-time employed.
Sex	Sex of respondent.
Self Emp	Indicator whether the respondent is self employed.
Day of Wk	Day of week of the interview.
Family income	Family income of the household.

Table 19: Abnormal returns to portfolios sorted on TA

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to the average deviation of temperature anomalies TA. Each month t, we sort U.S. states into four or five groups 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. Portfolio 1 includes the returns of firms operating in states experiencing the lowest values of TA (cold states). Portfolios 4 or 5 include those firms in states experiencing the highest values of TA (warmer states). We group the middle portfolios together by equal-weighting their respective returns and denote them as either "Portfolios 2,3" or "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for combinations of the Fama-French 3, liquidity, betting against beta, momentum, and the Fama-French 5 factors. "Portfolio 1–5" or "Portfolio 1–4" reports the return difference between the least and most exposed portfolios. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. The sample period is from January 1993 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 12 lags.

Panel A: Quartile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.025	0.005	-0.005	-0.122	-0.090
	(0.099)	(0.087)	(0.087)	(0.090)	(0.085)
Portfolios 2, 3	0.008	-0.044	-0.032	-0.104	-0.101
	(0.078)	(0.061)	(0.060)	(0.073)	(0.066)
Portfolio 4	0.015	-0.020	-0.037	-0.060	-0.046
	(0.109)	(0.111)	(0.116)	(0.127)	(0.116)
Portfolio 1 - 4	0.010	0.025	0.031	-0.063	-0.043
	(0.160)	(0.169)	(0.174)	(0.196)	(0.159)

Panel B: Quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	-0.020	-0.040	-0.040	-0.134	-0.082
	(0.084)	(0.079)	(0.077)	(0.086)	(0.081)
Portfolios 2, 3, 4	0.046	-0.001	-0.000	-0.059	-0.044
	(0.072)	(0.056)	(0.057)	(0.066)	(0.049)
Portfolio 5	-0.075	-0.108	-0.120	-0.159	-0.147
	(0.110)	(0.108)	(0.111)	(0.122)	(0.117)
Portfolio 1 - 5	0.055	0.068	0.080	0.025	0.065
	(0.144)	(0.152)	(0.153)	(0.184)	(0.155)

Table 20: Abnormal returns to portfolios sorted on deviations in mean precipitation

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to the average deviation of precipitation anomalies. Each month t, we sort U.S. states into four or five groups based on their realization of average precipitation. 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 precipitation (lower abnormal rainfall). Portfolios 4 or 5 include those firms in states experiencing the highest values of precipitaion (higher abnormal rainfall). We group the middle portfolios together by equal-weighting their respective returns and denote them as either "Portfolios 2,3" or "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for combinations of the Fama-French 3, liquidity, betting against beta, momentum, and the Fama-French 5 factors. "Portfolio 1–5" or "Portfolio 1–4" reports the return difference between the least and most exposed portfolios. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. The sample period is from January 1993 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 12 lags.

Panel A: Quartile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.093	0.058	0.054	0.007	-0.015
	(0.097)	(0.088)	(0.091)	(0.102)	(0.088)
Portfolios 2, 3	-0.019	-0.060	-0.066	-0.158	-0.123
	(0.072)	(0.058)	(0.058)	(0.053)	(0.057)
Portfolio 4	0.049	0.012	0.019	-0.039	-0.067
	(0.098)	(0.080)	(0.080)	(0.083)	(0.089)
Portfolio 1 - 4	0.044	0.046	0.035	0.046	0.052
	(0.131)	(0.135)	(0.138)	(0.154)	(0.133)

Panel B: Quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	-0.020	-0.040	-0.040	-0.134	-0.082
	(0.084)	(0.079)	(0.077)	(0.086)	(0.081)
Portfolios 2, 3, 4	0.046	-0.001	-0.000	-0.059	-0.044
	(0.072)	(0.056)	(0.057)	(0.066)	(0.049)
Portfolio 5	-0.075	-0.108	-0.120	-0.159	-0.147
	(0.110)	(0.108)	(0.111)	(0.122)	(0.117)
Portfolio 1 - 5	0.055	0.068	0.080	0.025	0.065
	(0.144)	(0.152)	(0.153)	(0.184)	(0.155)

Table 21: Abnormal returns to portfolios sorted on deviations in mean wildfire exposure

This table reports the monthly average excess returns for portfolios sorted based on firm exposure to the average deviation of wildfire risk (burning). Each month t, we sort U.S. states into four or five groups based on their realization of average wildfire risk. 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 wildfire risk (lower abnormal wildfire risk). Portfolios 4 or 5 include those firms in states experiencing the highest values of wildfire risk (higher abnormal wildfire risk). We group the middle portfolios together by equal-weighting their respective returns and denote them as either "Portfolios 2,3" or "Portfolios 2,3,4". We report the alphas of each portfolio after controlling for combinations of the Fama-French 3, liquidity, betting against beta, momentum, and the Fama-French 5 factors. "Portfolio 1–5" or "Portfolio 1–4" reports the return difference between the least and most exposed portfolios. We select firms that mention their headquartered state at least 5% of the time (the 10th percentile) in their 10-K filings, compared to mentions of all other states, and firms with more than 73% of their revenues generated in the U.S. The sample period is from January 1993 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 12 lags.

Panel A: Quartile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.034	0.008	0.013	-0.027	-0.042
	(0.096)	(0.079)	(0.079)	(0.083)	(0.082)
Portfolios 2, 3	0.032	-0.011	-0.011	-0.097	-0.061
	(0.070)	(0.069)	(0.069)	(0.069)	(0.067)
Portfolio 4	0.147	0.100	0.085	0.057	0.003
	(0.127)	(0.106)	(0.111)	(0.118)	(0.092)
Portfolio 1 - 4	-0.113	-0.092	-0.073	-0.084	-0.045
	(0.137)	(0.138)	(0.145)	(0.161)	(0.129)

Panel B: Quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.033	0.012	0.017	-0.020	-0.029
	(0.096)	(0.088)	(0.087)	(0.093)	(0.096)
Portfolios 2, 3, 4	0.006	-0.036	-0.039	-0.141	-0.095
	(0.075)	(0.067)	(0.068)	(0.060)	(0.064)
Portfolio 5	0.185	0.140	0.129	0.114	0.037
	(0.136)	(0.113)	(0.119)	(0.126)	(0.104)
Portfolio 1 - 5	-0.152	-0.128	-0.112	-0.134	-0.066
	(0.147)	(0.146)	(0.149)	(0.165)	(0.146)

A Internet Appendix

A.1 Temperature volatility

A.1.1 Dynamics

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 behaves in comparison to other metrics and weather variables. Our main comparison is the rolling average temperature anomaly, TA, since measures of average temperature have been widely used in the financial and economic literature (Choi et al. (2020);Cuculiza et al. (2024)). We also evaluate TAV against alternative temperature metrics, including the number of days above thresholds, intensity measures, precipitation, and wildfire risk.

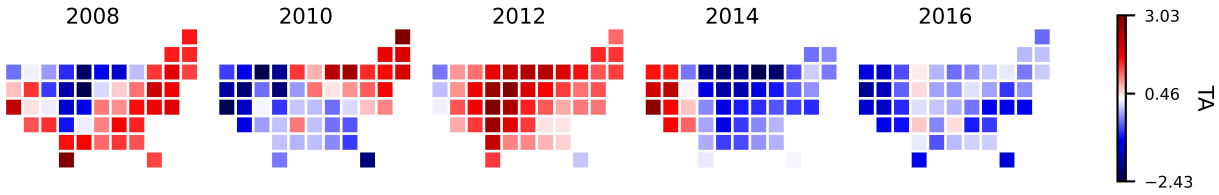
We construct the temperature metrics using maximum surface temperature data at roughly 0.0417 degrees latitude and longitude, about a 5 by 5 km grid, from NOAA's nClimGrid-Daily data (Durre et al., 2022). Aggregating this data to the state level, as described in the next section, uncovers distinct spatial and temporal variation for both TAV and TA, as illustrated in Figure 6.

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 7 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

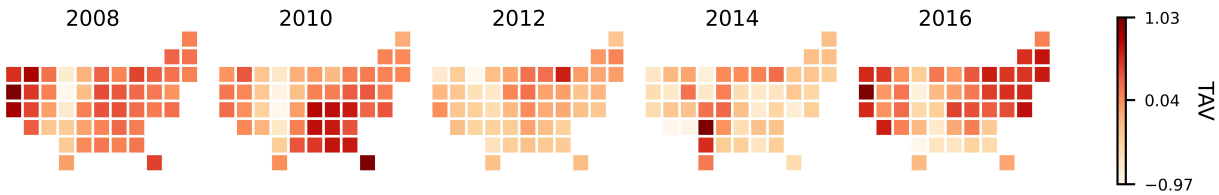
Figure 6: Geographic and time-series variation of temperature statistics

Figure 6 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.

(a) Yearly Mean Temperature Anomalies



(b) Yearly Standard Deviation of Temperature Anomalies



quarterly or yearly—which are consistent with financial data reporting periods—are provided in Appendix Section A.1.2.

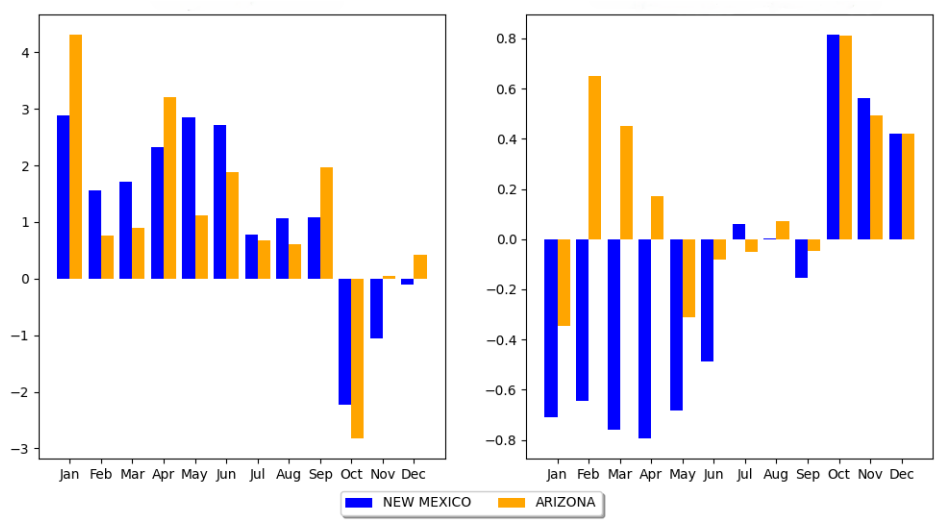
Next, we across the mean correlation coefficient between TAV and each of the three other physical risk metrics across all states by quarter, from 1993 to 2019. Panel (a) of Figure 8 shows the quarterly correlation between TA and TAV over the sample period, which fluctuates between 0.5 and -0.5, with an average correlation of -0.093. Panels (b) through (d) present the correlations between TAV, the absolute value of TA, average deviations in mean precipitation, and average deviations in wildfire risk, respectively,. Across all panels, the results indicate no stable relationship between TAV and the other metrics, suggesting that abnormal temperature volatility conveys distinct information.[16]

To better under the attributes of TAV, we test its ability to capture periods of extreme

[16]Using the absolute value of TA treats both colder-than-normal and hotter-than-normal temperatures as abnormal.

Figure 7: 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.

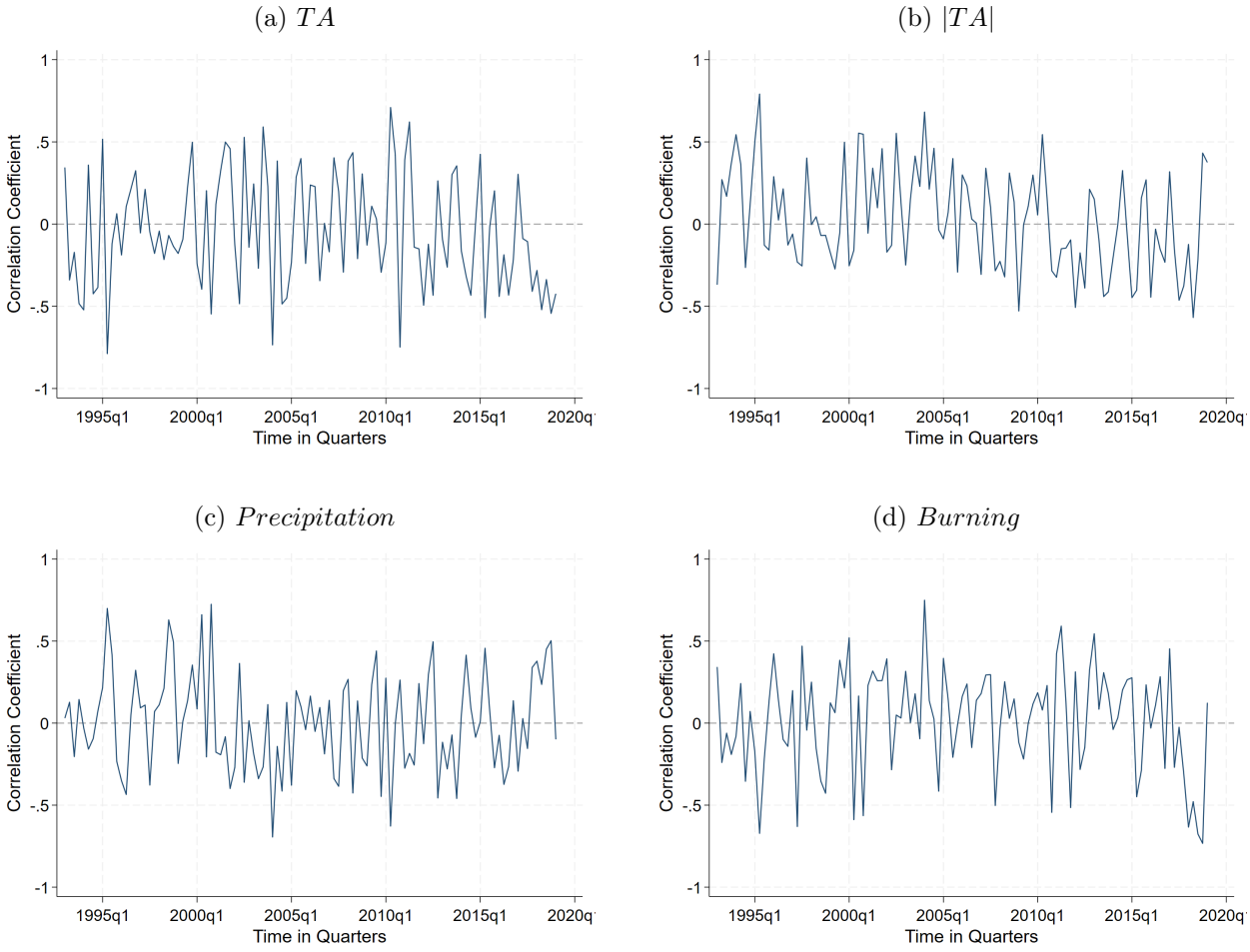


and intense temperatures, benchmarking it against the conventional 90-day rolling temperature anomaly TA. To quantify the number of unusually cold and hot days by specific dates (day d, month m, year y) and locations, we examine the temperature anomaly distribution from 1993 to 2019 for each state s, following the steps described in Section 1. Then, using matching percentile pairs from the historical 25-year rolling temperature anomaly distribution, we define extreme temperature days as those below the 2.5th to 30th percentiles for cold days, and above the 70th to 97.5th percentiles for hot days. These state-specific percentiles align with corresponding calendar quarters, reflecting different frequencies and intensities of temperature extremes. We then determine the *number of days* in a quarter 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 or 32°C threshold, associating

Figure 8: Quarterly correlation between TAV and other weather variables

This figure presents the monthly correlation between TAV, $|TA|$, TA, precipitation, and burning from 1993 to 2019.



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, TAV and TA. Figure 9 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, 2.5th and 97.5th). 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 two additional days of temperature extremes in a quarter. In contrast, TA displays a notably weaker relationship with the frequency of extreme temperature days.

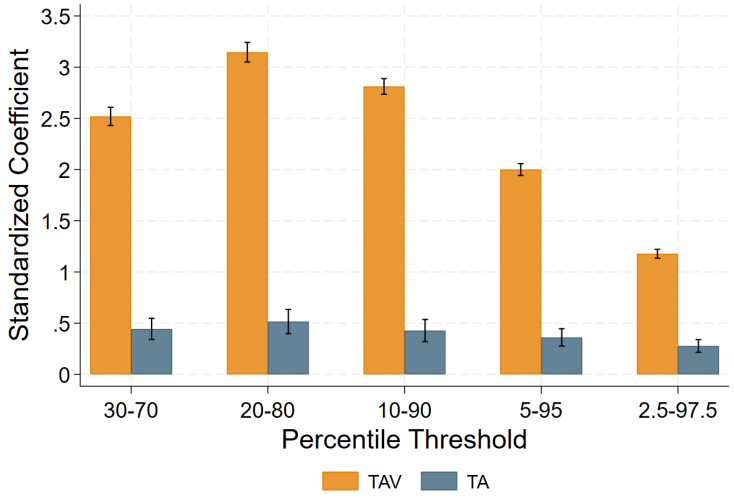
Next, we focus on the right tail of the temperature anomaly distribution which is relevant as most extant literature only studies heat extremes. Instead of counting the number (*frequency*) of extreme days, we explore how TAV and TA relate to the *intensity* or *severity* of extreme temperatures on days surpassing a defined threshold. Investigating severity is important because the magnitude of these exceedances is relevant for the magnitude of damages.[17] 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 effects on human behavior and economic outcomes. To calculate intensity, we again use percentile thresholds from a 25 year rolling historical window—specifically the 70th, 80th, 90th, 95th, and 97.5th percentiles—of the temperature anomaly distribution for each state and quarter. These thresholds are then applied to the period, 1993–2019 in a rolling fashion, to compute the mean anomaly of the days exceeding these thresholds within a given month, thus capturing the severity of extreme temperatures.

We next focus on the right tail of the temperature anomaly distribution, consistent with the literature's emphasis on heat extremes. Rather than counting the frequency of extreme days, we examine how TAV and TA relate to the intensity or severity of extreme

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

Figure 9: Capturing dynamics at both tails of the distribution

This figure displays the standardized coefficients of TAV (orange) and TA (blue), derived from regression analysis where the number of extreme days in a quarter and state is regressed on either TAV and TA. The coefficients are then "standardized" by multiplying each by their respective metrics' standard deviation. We define extremes by calculating the rolling 25-year percentile pairs of temperature anomalies for each state and quarter: the 2.5th and 97.5th percentiles, 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 quarter from 1993 through 2019 for each state. This graph reports the coefficients on TAV and $TA$of the regression $y_{s,[q,y]} = \beta \cdot \text{TA}_{s,[q,y]}$ and $y_{s,[q,y]} = \beta \cdot \text{TAV}_{s,[q,y]}$, where y is the number of extreme temperature days based on the percentile pairs for each unique combination of month, year, and state (q, 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.



temperatures on days that exceed threshold values. Measuring severity matters because larger anomaly magnitudes plausibly generate greater damages.[18] As climate change drives ever higher temperature records, capturing severity, not just incidence, becomes increasingly relevant for understanding impacts on human behavior and economic outcomes. To quantify intensity, we use the same rolling 25-year historical percentiles, the 70th, 80th, 90th, 95th, and 97.5th, for each state and quarter. For each threshold, in each month from 1993 to 2019, we calculate the mean anomaly on days exceeding that cutoff.

To examine how temperature metrics relate to the intensity of extreme anomalies, we regress the state-level quarterly mean temperature anomaly, conditional on exceeding each of the five percentile thresholds, on both TAV and TA. Figure 10 shows the standardized coefficients, which reflect the strength of each metric's association with temperature intensity. We find that TAV more strongly captures the severity of extreme anomalies at the distribution's tails. Specifically, a one-standard deviation increase in TAV is associated with about a 0.3 degree rise in the mean temperature anomaly on extreme days. This relationship becomes even stronger at higher (more extreme) thresholds.

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. For each quarter we calculate the number of days exceeding these thresholds for each state between 1993 and 2019. We then regress the number of days that exceed the threshold on TA and TAV. Figure 11 presents the standardized coefficients of TAV (orange) and TA (blue) in representing the number of days above the threshold. The results demonstrate an effect size TAV half as much in comparison to TA in its representation of days above the threshold. One reason may be due to heatwaves which can occur for a string of days, pushing up values of average temperature anomalies.

[18] Somanathan et al. (2021) document sharper drops in worker productivity when temperatures exceed 35°C rather than just 30°C.

Figure 10: Intensity of extreme hot temperatures

This figure displays the magnitude of the relationship between the intensity of hotter than normal temperatures to TAV (orange) and TA (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 the rolling 25-year percentile pairs of temperature anomalies for each state and quarter: the 97.5th, 95th, 90th, 80th, and 70th 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 $y_{s,[q,y]} = \beta \cdot \text{TA}_{s,[q,y]}$ and $y_{s,[q,y]} = \beta \cdot \text{TAV}_{s,[q,y]}$, where y is the average temperature anomaly for each unique combination of quarter, year, and state (q, y, s). The coefficients suggest TAV more effectively represents intense temperatures relative to TA.

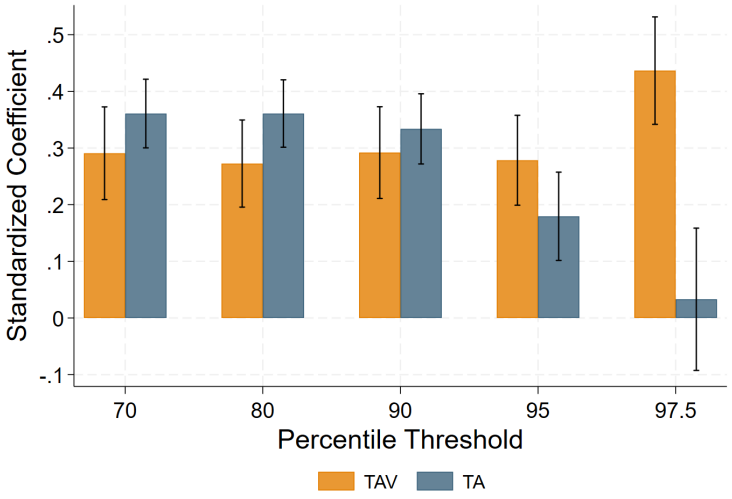
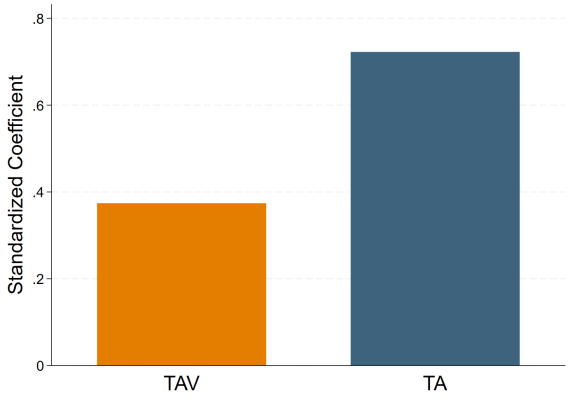


Figure 11: Representing the number of days above 30°C

This figure displays the magnitude of the relationship between the number of days in a quarter over 30°C in a state to TAV (orange) and TA (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 $y_{s,[q,y]} = \beta_1 \cdot \text{TA}_{s,[q,y]} + \beta_2 \cdot \text{TAV}_{s,[q,y]} + \omega$, where y is the number of days above 30°C per quarter, year, and state (q, y, s). ω represents a set of quarter fixed effects.



A.1.2 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:

$$T_{s,[d,m,y]} = \sum_{i=1}^{N_s} w_i \cdot T_{i,[d,m,y]}, \tag{11}$$

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 $1/N_s$.[19] Thus, $T_{s,[d,m,y]}$ is an equally weighted average

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

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.1.3. 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 6 highlights the state-level measures of TA and TAV across the US for the selected years 2008, 2010, 2012, 2014, and 2016. 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.

A.1.3 Alternative construction of temperature variables

In our primary analysis, 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.

A natural choice for weighting within our empirical context are population-based weights. Population-based weights prioritize human experiences; thus, greater variability in a densely populated state holds more significance than in a sparsely populated one.

A.2 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.[20] 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.[21] 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.[22] 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, such as changes in temperature patterns.[23] This challenge stems from the difficulty in deter-

[20]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.

[21]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.

[22]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.

[23]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

mining 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. 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 A.2.1 illustrates how a firm can use TAV to report its exposure to temperature, and Section A.2.2 presents a portfolio construction methodology that minimizes an investor's exposure to the future evolution of TAV.

A.2.1 Reporting

The first exercise involves a situation where a company, adhering to the emerging sustainability disclosure standards,[24] 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.

address a broader range of climate-related risks and opportunities".

[24]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).[25] 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 pro-

[25]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.

jections 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, 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.[26]

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.[27] 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.

[26]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.

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

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 22 report the percentage of 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.

A.2.2 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

Table 22: Reporting exposure to changes in temperature variability

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.

TAV Exposure	State	TAV	Firm 1 Installations	Firm 1 Exposure	Firm 2 Installations	Firm 2 Exposure
	(1)	(2)	(3)	(4)	(5)	(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%	

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 23 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 A.2.1, 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 23, 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.

Table 23: Optimizing portfolio temperature exposition

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.

		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