The Effects of Volatile Temperatures on Equity Returns and Firm Performance*

Leonardo Bortolan[1] Atreya Dey[2] Luca Taschini[3,4]

[1] *University of Bologna*

[2] *University of Cambridge, Judge Business School*

[3] *University of Edinburgh Business School*

[4] Grantham Research Institute

London School of Economics

Abstract

We construct a measure of abnormal temperature variability, defined as deviations in intra-month anomalies from a rolling historical baseline, capturing transitory and idiosyncratic temperature shocks. Firms subject to greater temperature variability experience lower revenues and fewer hours worked, driven by reductions in household spending and labor supply. An equity strategy based on cross-sectional variation in abnormal temperature variability yields a realized market-adjusted alpha of 4.9% annually, attributable to cash-flow news. Despite the observed return differential, we find informational frictions in the form of greater return volatility, stemming from uncertainty about firm-level impacts and disagreement over the materiality of temperature risks.

Keywords: Climate Finance, Temperature Variability, Equity Returns, Cash-Flow News, Rational Inattention.

JEL classification codes: Q54; G12; G14; G32.

*The authors' email addresses are leonardo.bortolan@studio.unibo.it, a.dey@jbs.cam.ac.uk and luca.taschini@ed.ac.uk.

1 Introduction

Climate change is shifting long-run average temperatures, intensifying extreme realizations, and increasing temperature variability (Hansen et al., 2012). A growing literature shows that equity markets price exposure to slow-moving changes in average temperature (Bansal et al., 2019). In contrast, evidence on short-run, realized temperature disruptions, such as extreme fluctuations and temperature variability, is limited. Despite the increasing frequency and intensity of temperature fluctuations, existing studies point to a weak contemporaneous return response to these temperature realizations (Cuculiza et al., 2025; Addoum et al., 2023).

This weak contemporaneous pricing is puzzling when considering three facts. First, short-run temperature disruptions have first-order real effects on firms via both supply and demand channels (Pankratz and Schiller, 2024; Lee and Zheng, 2025). Second, other markets and intermediaries respond actively to these realizations. For example, mutual funds tilt portfolios following local heat waves, derivatives prices embed temperature forecasts, and climate-related attention rises with hotter temperatures (Alekseev et al., 2022; Schlenker and Taylor, 2021; Choi et al., 2020). Third, the associated cash-flow losses show up in fundamental outcomes, but equity prices appear to adjust mainly when those losses are revealed in earnings (Pankratz et al., 2023; Addoum et al., 2023). Given these real effects, does contemporaneous pricing operate along a different dimension of the changing temperature distribution?

We argue that the relevant disruptions are localized and idiosyncratic, creating cross-sectional winners and losers that rotate across firms over time. We therefore construct a measure of abnormal temperature variability—an increasingly salient feature of climate change (Kotz et al., 2021; Yang and Schoder, 2025)–which captures unusual temperature swings and disruptive extremes more closely than measures based on mean temperature deviations (Katz and Brown, 1992).[1] By measuring short-term deviations from localized historical patterns, we capture frequent, plausibly exogenous temperature shocks (Auffhammer et al., 2013; Dell et al., 2014) and study their effects on US equities. This approach contrasts with studies that treat temperature exposure as a firm characteristic associated with a risk premium (e.g.,

[1]Existing approaches rely on average deviations, overlooking the role of variability—rather than just the level—of temperature anomalies in driving operational disruptions, as documented in (Yang and Schoder, 2025; Bettarelli et al., 2025; Donadelli et al., 2019).

Bansal et al., 2019; Acharya et al., 2022; Cuculiza et al., 2025).

To isolate firm-level exposure to abnormal temperature variability, we sort US states each month by realized variability quantiles and map firms to states based on their geographically concentrated operating locations, as measured using 10-K disclosures. Exposure is transitory, with little persistence across months and locations.[2] Using this state sorting strategy, we form value-weighted quantile portfolios and find that firms whose operations coincide with greater abnormal temperature variability underperform those with lower exposure in the same month. The corresponding long-short portfolio produces a market-adjusted return of 4.9% per year. In contrast, we find no significant alphas when exposure is constructed using alternative weather measures such as mean temperature deviations, precipitation, or wildfire risk. We confirm the contemporaneous return relation with placebo tests that preserve the distributional structure of the temperature data, double-sorts on temperature and size, Fama and MacBeth (1973) regressions controlling for firm characteristics and other climate risks, and tests showing that the alpha is not subsumed by anomalies documented in Chen and Zimmermann (2022).

Having established a contemporaneous return response, we ask whether it reflects cash-flow or discount-rate variation. Campbell (1991) decompositions show that the return differential is driven primarily by cash-flow news rather than discount-rate news. We corroborate this finding with direct evidence on firm-level fundamentals. A one-standard-deviation increase in abnormal temperature variability is associated with a loss of $1.54 million in annual revenues and $0.5 million in annual profits for the average firm in our sample. Effects vary across industries, with negative responses concentrated in Business Equipment, Construction, Manufacturing, Durables, Finance, and Retail Shops, and positive revenue effects in Utilities and Energy.

We then investigate the economic mechanisms behind this return response by examining the real effects through which abnormal temperature variability affects firm cash flows. Consistent with evidence that short-run temperature influences consumption and hours worked (Starr, 2000; Graff Zivin and Neidell, 2014; Neidell et al., 2021), we find heterogeneous effects

[2]The one-month Spearman rank autocorrelation is approximately 0.20, falling to zero by month two, and state transition matrices show frequent reshuffling across variability percentiles, implying substantial rotation in the set of regions (and therefore firms) subject to the temperature shock.

of variability on household spending and labor input. Using the US Consumer Expenditure Survey, we estimate that a one-standard-deviation increase in abnormal temperature variability reduces household spending by $110 per year. With roughly 20,775 households surveyed each year, this corresponds to an aggregate decline of $2.28 million.[3] The spending response is concentrated in Non-durables, Durables, and Apparel, while Utility expenditures increase, mirroring the sectoral revenue patterns in firm data. Using the American Time Use Survey, we also find that workers in temperature-sensitive sectors (Construction, Manufacturing, and Transport) work about 2.6 fewer minutes per day per one-unit increase in TAV relative to workers in less exposed sectors. This magnitude aligns closely with existing estimates of hours-worked responses to extreme temperatures Neidell et al. (2021).

We next examine how markets process these disruptions when they occur and translate them into expectations about firm cash flows. Abnormal temperature variability increases climate-related attention: news coverage intensifies, Google search activity rises, and affected firms discuss climate more frequently in earnings calls (Engle et al., 2020; Sautner et al., 2023). Attention alone, however, does not translate into uniform belief updating. Using survey data, we show that while individuals report greater exposure to climate impacts following heightened temperature variability, they do not update beliefs about the existence of climate change. The uneven updating implies disagreement about these consequences, increasing valuation uncertainty. This is reflected as higher firm-specific return volatility and greater dispersion in analyst forecasts, even after controlling for public attention. Analysts also underestimate the earnings effects, leading to negative earnings surprises. As in Kruttli et al. (2025), this pattern reflects impact uncertainty—the difficulty of translating realized weather disruptions into expectations about firm cash flows.

These results are consistent with mechanisms of rational inattention and informational frictions. Abnormal temperature variability is transitory and rotates geographically, making its firm-level implications difficult to assess ex-ante. Although realizations attract attention when they occur, investors face impact uncertainty—the difficulty of translating temperature variability into expected cash-flow consequences—which leads to heterogeneous belief updat-

[3]Scaling this estimate to the population in state of Texas as of 2019 suggests a potential reduction of over $1 billion in consumer expenditures.

ing rather than consensus pricing. Unlike discrete, high-salience disasters such as hurricanes, which can act as salient learning events and support a risk premium (Kruttli et al., 2025), vulnerability to abnormal temperature variability is widespread but realized exposure is sporadic. This episodic exposure makes cash-flow effects hard to anticipate and sensitive to prior beliefs. Investors therefore allocate limited attention to this signal ex-ante, and prices adjust on impact through cash-flow news rather than via a persistent discount-rate channel.

This study advances the climate finance literature in two main ways. First, we develop a novel measure of temperature exposure—abnormal temperature variability— and show that when short-run weather disruptions are measured as innovations in intra-period variability relative to local seasonal baselines, equity returns adjust contemporaneously in the cross-section, with economically meaningful implications for prices, firm performance, and investor behavior. Second, we identify the economic and informational channels through which these effects arise. Related studies (Addoum et al., 2020; Pankratz et al., 2023; Acharya et al., 2022; Pankratz and Schiller, 2024) examine temperature effects using predetermined thresholds or the right-hand tail realizations and construct exposure at scales ranging from individual facilities to national aggregates. In contrast, our measure operates at an intermediate regional level and benchmarks realized variability against rolling, location-specific historical baselines. This construction yields short-lived, idiosyncratic shocks that are less susceptible to climatic trends that may drive bias in threshold- and bin-based measures (Jones et al., 2026).

Our emphasis on contemporaneous realized returns, informational frictions, and uncertainty distinguishes this work from Addoum et al. (2023) and Pankratz et al. (2023). Using absolute temperature measures, these studies document seasonal and industry-specific effects on profitability but find little contemporaneous adjustment in equity prices; instead, price responses occur when cash-flow consequences are revealed in earnings. We complement this evidence by showing that, when temperature disruptions are measured as changes in localized abnormal temperature variability, equity returns adjust contemporaneously in the cross-section. At the same time, we reconcile delayed price adjustment by highlighting informational frictions. While abnormal temperature variability raises attention among both retail (Choi et al., 2020) and institutional investors (Alekseev et al., 2022), investors face substantial uncertainty in mapping these realizations into firm-level cash-flow implications

(Kruttli et al., 2025), which sustains disagreement and slows incorporation into prices. This disagreement is further shaped by heterogeneity in beliefs about climate change (Bakkensen and Barrage, 2022).

Further, our findings offer a distinct perspective relative to studies linking temperature exposure to equity returns. Cuculiza et al. (2025) show that firms exposed to gradual changes in average temperature anomalies earn lower returns, with adjustment unfolding over extended horizons, consistent with market underreaction to slow-moving temperature trends. Acharya et al. (2022) and Bae et al. (2023) document a positive risk premium for forward-looking exposure to heat stress and future temperature oscillations, respectively. By contrast, we show that markets respond contemporaneously to abnormal temperature variability, with returns reflecting realized, idiosyncratic cash-flow shocks rather than compensation for systematic temperature risk. Consistent with this interpretation, we find no contemporaneous return response to average temperature deviations used by Cuculiza et al. (2025), underscoring a fundamental difference between pricing responses to short-run variability and slow-moving changes in mean temperature conditions.

This paper is organized as follows. Section 2 details the construction of our metric. Section 3 describes our data sources and how we identify affected firms. In section 4 we explain our identification strategy, present our cross-sectional return tests, and our results analyzing the effect of our metric on firm-level cash flows. Section 5 determines various channels through which abnormal temperature variability operates. Section 6 concludes.

2 Temperature anomalies and variability

Our objective is to measure short-term, location-specific temperature variability that contemporaneously affects firms and market participants. Rather than analyzing whether a region is hotter or colder than usual, we examine whether temperature conditions are unusually variable relative to seasonal historical patterns. This approach ensures that we measure realizations against regional expectations to capture unexpected shocks.

Our emphasis on variability is motivated by the growing consensus that climate change affects the entire temperature distribution—shifting the mean, changing dispersion and tail

risk—rather than purely shifting the mean. Hansen et al. (2012) and (Wu et al., 2025) suggest that climate change: (i) broadens the temperature distribution to encompass extreme abnormal temperatures, and (ii) increases the frequency of sudden swings between hot and cold temperatures. The economic literature has shown that measures similar to the first feature—long-term shifts in the dispersion (second moment) of the temperature distribution—have negative effects on welfare, productivity, innovation, migration, and growth (Cruz and Rossi-Hansberg, 2023; Donadelli et al., 2019). Temperature swings, on the other hand, have more limited evidence of direct economic damage, although they are linked to lower overall economic growth (Kotz et al., 2021; Linsenmeier, 2022). Generally, this focus on variability is supported by statistical theory, which demonstrates that the frequency of extreme events is more sensitive to changes in the variability of climate than to changes in its mean (Katz and Brown, 1992).

Building on this evidence, we analyze temperature variability as a complementary dimension of weather realizations. Specifically, we calculate abnormal intra-period fluctuations by measuring the dispersion of daily anomalies against a rolling, location-specific baseline. This design isolates innovations in intra-period variability relative to local expectations, rather than using temperature levels or mechanically trending exceedance counts. We expect that capturing unexpected changes in the within-period distribution of temperatures will allow us to identify plausibly exogenous, time-place-specific disruptions that contemporaneously impact both firm operations, investor attention, and ultimately equity returns.

Existing climate-finance studies typically focus on either mean temperature anomalies or threshold-based exceedances. For example, Choi et al. (2020), Cuculiza et al. (2025), and Kelly et al. (2005) rely on mean anomaly measures which abstract from variation within the month. Other studies, such as Pankratz et al. (2023) and Addoum et al. (2020), measure temperature anomalies by counting the number of days exceeding 30°C within a given period, therefore focusing on the frequency of heat extremes. While informative, both approaches can understate the role of temperature fluctuations (i.e. realized weather shocks): central-tendency measures smooth over high-frequency variation, while threshold approaches rely on arbitrary cut-offs, down-weight cold extremes, and produce zero-inflated distributions in temperate regions and seasons. Additionally, Jones et al. (2026) offers a useful reminder

that nonlinear temperature transformations can, in some context, incorporate slow-moving, predictable shifts in exposure that correlate with baseline climate. To focus on short-run disruptions, we propose a metric that benchmarks realized intra-period variability against a rolling, location- and calendar-specific expectation, so that our measure captures unexpected deviations from local seasonal conditions.[4]

To construct our metric, we begin by defining temperature anomalies as deviations from historical averages, specific to a location and time. Calculating anomalies by differencing observed temperatures from their local baselines isolates the short-term, location-specific weather shocks that are plausibly exogenous and improves identification. This also removes time-invariant, location-specific climate features that could bias estimates of temperature effects on economic and financial outcomes (Dell et al., 2012).

For example, Choi et al. (2020) use a 10-year rolling window, while Pankratz and Schiller (2024) anchor expectations to the start of a supply-chain relationship. We define temperature anomalies as a departure from a 25-year rolling historical average of daily maximum temperatures at a given location:[5]

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

where $TA_{s,[d,m,y]}$ represents our measure of the daily temperature anomaly on a specific day d, in month m, year y, and location s, calculated from the observed maximum temperature $T_{s,[d,m,y]}$. For a given year 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 preceding 25 years using a ± 1 day window around each calendar day to reduce measurement error while

[4]More generally, nonlinear temperature transformations can embed slow-moving, baseline-climate–correlated shifts in measured exposure (Jones et al., 2026). When the object of interest is contemporaneous disruption, it is therefore useful to benchmark realizations against local expectations. We do so with a rolling, location- and calendar-specific baseline, so the proposed metric captures departures from expected seasonal variability rather than slow-moving exposure shifts.

[5]The National Oceanic and Atmospheric Administration (NOAA) and the World Meteorological Organization recommend 30-year periods to calculate climate normals, as this length smooths out inter-annual variability, cyclical phenomena such as El Niño, and decadal oscillations. At the same time, survey evidence from Akerlof et al. (2013) suggests that individuals perceive shifts in seasonal weather patterns over horizons closer to 20 years. Our 25-year window balances these considerations. In the Internet Appendix, we show that our main empirical results are robust to alternative specifications using 20- and 30-year rolling windows, confirming that the choice of 25 years does not drive our findings.

preserving the day-of-year seasonal profile. As a result, temperature anomalies exhibit both time-series and cross-sectional variation since $\overline{T}_{s,[d,m]}^{[y-25,\,y-1]}$ is not a constant.

To obtain a monthly, location-specific measure of the day-to-day temperature anomaly, we average the daily anomalies within each month:

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

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

We introduce Temperature Anomaly Variability (TAV), defined as the deviation of the intra-month variability of daily temperature anomalies from a location- and month-specific baseline. This baseline is the 25-year rolling average of the within-month standard deviation for the same location and calendar month. 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 measures how much temperature anomalies fluctuate around the monthly mean at that location.

We next compute TAV:

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

where $\overline{\sigma}(TA_{s,[m]})^{[y-25,,y-1]}$ denotes the 25-year rolling average of the within-month standard deviation for the same location s and calendar month m (years $y-25$ to $y-1$). By construction, TAV measures deviations in temperature anomaly variability from local 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 unusually high intra-month variability, and negative TAV indicates low variabil-

ity.[6] Positive TAV therefore corresponds to months characterized by more dispersed daily temperature anomalies, reflecting more pronounced short-term fluctuations. In Section B.1.1 of the Internet Appendix, we document the statistical properties of TAV and compare them with those of TA.

3 Data

Our sample is constructed by merging data from several databases covering financial, economic, survey, and climate data. Summary statistics for all variables are presented in Table 1, and descriptions are provided in Table A.1 in the Appendix.

3.1 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 US from 1951 to 2019. The 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 alternatives like Berkeley Earth due to its finer resolution and US focus.[7]

For our empirical analysis, we assign equal weight to each grid cell within state borders to construct state-level temperature data. To also construct a country-level measure of temperature, we weight state-level temperatures by population obtained via the "POP" code from the Federal Reserve Bank of St. Louis, available from 1950 onward. This process is explained in Section B.1.2 of the Internet Appendix.

[6] Our approach differs from Donadelli et al. (2019), who compute annual volatility of temperature levels relative to a constant, pre-industrial baseline. By contrast, we focus on variability in temperature anomalies relative to rolling, local baselines, aligning the metric with recent experience and localized conditions and avoiding aggregation bias from national-level data (Auffhammer et al., 2013).

[7] nClimGrid offers significantly higher spatial resolution than Berkeley Earth, which provides global data at a coarser 1 degree by 1 degree grid—roughly 100 km by 100 km.

3.2 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 are sourced from the Institutional Brokers Estimate System (I/B/E/S).

3.3 Firm geographic concentration

One difficulty in measuring the effects of temperature on firms is that their headquarters may not represent the firm's center of operations. To adjust our strategy for firm-level geographic dispersion, we use the methodology outlined in Garcia and Norli (2012) and Bernile et al. (2015) who develop a 10-K-based measure of firm local exposure. We parse the annual Form 10-K filings of the firms in the dataset and identify the number of times a US state is mentioned in sections 1A, 2, 6, and 7. The firm-headquarter citation count is calculated by dividing the total number of mentions of the headquartered state by the total mentions of all 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, Near Headquarter. 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 the calculated 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 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.

3.4 Other data

We obtain precipitation and wildfire risk data from the Gridded Surface Meteorological (gridMET) dataset. We average precipitation and the wildfire 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 2. 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 US 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).

4 Returns and firm performance

In this section, we outline our empirical strategy and conduct a set of cross-sectional return exercises to compare the realized returns of firms most and least affected by abnormal temperature variability. We next investigate the drivers of the return differential.

4.1 Empirical strategy

Our primary outcome variables—equity returns and profitability—are measured at the firm level. To assign geographic exposure, we approximate each firm's location using the state in which it is headquartered and match firms to our state-level temperature metrics. Because detailed data on firms' operations and customer locations—two channels through which temperature may affect performance—are unavailable, we adopt the methodology from Garcia and Norli (2012). Specifically, we exclude firms with high geographic diversification from the analysis. We omit firms that frequently mention states other than their headquarter location and firms with substantial international revenue to ensure our analysis focuses on domestic temperature exposure.

We leverage monthly abnormal temperature variability as plausibly exogenous weather shocks (Auffhammer et al., 2013), allowing us to identify their effects on firm performance. By comparing recent temperature values to historical distributions from the same location and time of year, we control for time-invariant, geography-specific climate baselines. This approach isolates deviations from long-run historical norms, capturing short-term weather variation while accounting for location-specific climate baselines.

To show that cross-sectional exposure to temperature variability is geographically and temporally transient, i.e., rotating across states from month to month, we compute state-level TAV each month and rank states into quartiles or quintiles based on their contemporaneous realized exposure. Table 2 presents state transition matrices where each entry reflects the percent of time a state moves from one percentile tier at month t to another at $t+1$. The rows indicate starting percentiles, and the columns show subsequent percentiles at $t+1$. The roughly equal transition probabilities indicate that relative exposure to abnormal temperature variability is transitory in both space and time, in that states shuffle frequently between high

and low TAV. Table 3 further highlights this shuffling in that the rank autocorrelation of exposure decays rapidly. In other words, while there is modest persistence when using a one-month lag (0.2), the correlation coefficient drops to near-zero by the second month.

The transition matrices and Spearman rank correlations jointly reveal that cross-sectional exposure to temperature variability is short-lived. While a region may exhibit elevated exposure relative to the cross-section in period t, this positioning shifts quickly. The absence of persistence supports an interpretation of temperature variability as a sequence of realized shocks rather than a persistent regional attribute. Under standard asset-pricing logic, realized local weather shocks (captured here by abnormal temperature variability) are predominantly idiosyncratic and therefore diversifiable, so they should not command a risk premium. Our empirical strategy therefore does not test whether temperature variability risk is priced in expectation; instead, we assess whether realized weather shocks affect firm performance and whether equity prices adjust promptly to their operational implications.

Endogeneity could theoretically arise from firm-specific adaptations, like infrastructure investment, which are difficult to observe. We assume, however, that these responses are sticky and evolve slowly. This assumption is corroborated by Pankratz and Schiller (2024), who document that adaptation mechanisms, such as restructuring supply chains, typically unfold over longer horizons. To address this concern, our panel regressions include firm-by-year fixed effects, absorbing unobservable characteristics related to adaptation. In addition, our construction of abnormal temperature variability using a rolling 25-year baseline helps mitigate concerns that long-term trends in technological adaptation might bias results—a limitation of approaches relying on static historical baselines.[8]

Temperature variability is often linked with other weather phenomena, such as precipitation extremes (Allan and Soden, 2008), raising concerns that our estimates may partly reflect the joint effects of both variables. To allay concerns of omitted variable bias, we control for precipitation and a wildfire risk metric derived from the US National Fire Danger Rating System.

[8] As discussed in the Internet Appendix B.2.2, we test the robustness of our findings using alternative 20- and 30-year rolling windows.

4.2 Cross sectional returns

To examine the cross-sectional return response to idiosyncratic temperature shocks, we use a conditional sorting strategy based on realized state-level abnormal temperature variability. In each month t, we partition the 48 contiguous US states into quantile groups based on the distribution of realized TAV for that month.[9] Firms are then assigned to value-weighted quantile portfolios (quartiles or quintiles) according to the TAV of the states in which they operate.[10] The lowest quantile portfolio comprises firms whose operational footprints coincide with states experiencing the lowest TAV that month, while the highest quantile portfolio captures firms operating in states experiencing the greatest temperature variability. We then construct long-short (L/S) returns by subtracting the returns of firms in the highest quantile portfolio from those in the lowest. By construction, this cross-sectional sort is neutral to aggregate market dynamics. By differencing out common macro-financial drivers, the spread isolates the return differential driven by the spatial realization of abnormal local temperature in that month.

Figure 3 plots the L/S abnormal returns from portfolios rebalanced monthly on contemporaneous state-level realizations of TAV, reporting both quartile and quintile sorts. The figure shows that conditioning on variability generates a positive return spread. Specifically, in a given month, firms whose operational footprints coincide with low realized TAV outperform firms exposed in that month to high realized abnormal temperature variability.

The first columns of Panels A (quartile sort) and B (quintile sort) in Table 4 report market-adjusted abnormal returns for each portfolio. The table reports monthly abnormal returns for the low- and high-TAV portfolios, as well as the intermediate portfolios, and the corresponding L/S spread. The L/S abnormal return ranges from 34 to 40 basis points per month, equivalent to 4.21% and 4.81% per year. The annualized Sharpe ratio of the market-adjusted L/S strategy is 0.56.

We next assess whether common risk factors account for the abnormal return pattern of the TAV-sorted L/S portfolios. The remaining columns of Table 4 report the risk-adjusted

[9] The nClimGrid-Daily product is only available for the contiguous US.

[10] We use the geographic concentration measure described in Section 3.3 and exclude firms with highly dispersed operations, defined as firms that mention their headquartered state less than 5% of the time (the 10th percentile) relative to other states in their 10-K filings.

abnormal returns after controlling for standard factor models, including the Fama-French three-factor model (second column), Pástor and Stambaugh's liquidity factor (third), Frazzini and Pedersen's (Frazzini and Pedersen, 2014) betting against beta (fourth), and the Fama-French five-factor model augmented with Carhart's momentum factor (fifth). The results show that the return spread based on TAV is not explained by these factors; the L/S portfolio continues to exhibit statistically significant abnormal returns. This suggests that, in a given month, firms whose operations coincide with higher realized abnormal temperature variability underperform relative to those firms with lower exposure.

Overall, the L/S return spread reflects the market response to realized, idiosyncratic temperature shocks rather than compensation for ex-ante temperature risk exposure. Under a risk-premium framework, firms with greater temperature exposure should either command higher expected returns ex-ante, or the market should gradually learn to price that exposure over time. Kruttli et al. (2025), for example, documents that markets began demanding a premium for hurricane exposure following the "saliency shock" of Hurricane Sandy. To test for anticipatory pricing, we construct portfolios based on lagged TAV. A strategy going long low-TAV_{t-2} and short high-TAV_{t-2} firms yields statistically insignificant alphas. Sorting on TAV_{t-1} produces a significant, albeit smaller, alpha of 26.5 basis points (see Internet Appendix Section A.2). This short-term persistence aligns with the limited autocorrelation in TAV.

The absence of predictability at longer horizons suggests that abnormal temperature variability does not behave like a persistent risk factor. Instead, prices adjust on impact when shocks occur. This contemporaneous response is detectable because we use granular, realized fluctuations in temperature variability mapped to firms' operating footprints, rather than coarse averages or threshold exceedances (Addoum et al., 2023; Cuculiza et al., 2025). The lack of a premium is therefore consistent with the localized, idiosyncratic, and transitory nature of TAV, which, unlike regionally confined hurricane exposure, is geographically ubiquitous but temporally difficult to predict.

We next conduct robustness tests to confirm the main result. To address concerns of spatial correlation and to validate that the relationship is not spurious, we conduct placebo tests, as detailed in Appendix A.1. We preserve the empirical distribution of TAV but

randomly shuffle its monthly values, either across states (cross-section) or over time (time series), and repeat the portfolio sort 5,000 times for each permutation. After adjusting for the Fama-French three-factor model, fewer than 20 iterations generate greater abnormal returns than the original strategies. The placebo tests confirm that the return effects are driven by the precise coincidence of abnormal temperature variability with firms' operational footprints in both time and location, not by spurious spatial correlations or fixed state-level attributes. For further robustness, we estimate Fama-MacBeth regressions with a comprehensive set of firm- and state-level controls along with a climate news index in Internet Appendix B.2.1. Next, we address concerns related to firm size by performing a double sort on abnormal temperature variability and firm total assets in Internet Appendix B.2.1. We also conduct additional sorts using contemporaneous deviations in average temperature, precipitation, and wildfire risk, detailed in Internet Appendix B.2.4, confirming the that the return response is specific to abnormal temperature variability rather than to weather conditions more broadly defined.

Finally, we assess whether the abnormal returns are subsumed by known pricing anomalies. We regress the L/S returns from the quartile and quintile portfolios on the Fama-French 3-factor model, sequentially adding each of the 189 return anomaly predictors from Chen and Zimmermann (2022). Figure 4 shows histograms of the resulting t-statistics, with dashed lines marking the 5% and 10% significance thresholds. All abnormal return estimates remain statistically significant at the 5% level, except for two cases—announcement returns (Chan et al., 1996) and dividend seasonality (Hartzmark and Solomon, 2013)—which are significant at the 10% level and are also among the strongest signals in Chen and Zimmermann (2022). We further adjust for multiple hypothesis testing using the False Discovery Rate method from Benjamini and Yekutieli (2001), yielding a marginally lower critical P-value of 0.049. Overall, the persistence of statistical significance indicates that the TAV-sorted return spread is orthogonal to established anomaly predictors.

These results indicate that the information content of TAV is tied to the contemporaneous alignment between the realized temperature shock and the firm's operations. The return spread is strongest when abnormal temperature variability is realized and mapped to the firm's geographic exposure in the same month. Consistent with this interpretation,

the spread weakens markedly when the signal is lagged, disappears under random permutations in placebo tests, and is not replicated by alternative contemporaneous weather controls. This evidence points to price adjustments to idiosyncratic weather shocks as they materialize, rather than compensation for a persistent exposure.

Our findings complement and help reconcile existing evidence in the climate-finance literature. While studies such as Addoum et al. (2023) and Cuculiza et al. (2025) document economically meaningful effects of temperature on operating performance, they find no corresponding contemporaneous pricing response in equity returns. This divergence reflects a distinction in measurement and empirical design rather than a contradiction in results. Where prior approaches either aggregate facility-level temperature data or use national averages, that are less well-suited to isolating spatio-temporal shocks, our approach isolates abnormal temperature variability at specific geographies and the maps it to firms when those regions are most affected by temperature anomalies.

These L/S return patterns are consistent with a rational inattention framework, in which investors face information-processing capacity constraints and choose which information to attend to. Geographically rotating shocks such as TAV, where realized exposure shifts quickly across states, are largely diversifiable in broad portfolios but costly to track and map into firm-level implications in real time. As a result, investors may rationally place limited weight on these signals ex-ante and update valuations primarily when the shocks materialize. Abnormal temperature variability also appears to draw climate-related attention—explored in Section 5.2—and is accompanied by a negative contemporaneous return response on average. Consistent with this interpretation, markets do not treat TAV as a persistent factor, in contrast to spatially concentrated hazards such as hurricane risk, where exposure is more stable and more easily identified ex-ante.

4.3 Cash-flow effects

Having established a contemporaneous return response to realized TAV, we now disentangle the drivers of this price variation. Theory predicts that idiosyncratic and transitory shocks, such as abnormal temperature variability, should influence equity values primarily through firm fundamentals rather than through discount rates. We assess the relative importance of

cash flow and discount rate news in driving the return spread using the Campbell-Schiller VAR decomposition (Campbell, 1991). Additionally, we corroborate the decomposition evidence with measures of firm performance, including revenues and profitability.

4.3.1 Campbell-Schiller decomposition

We use the L/S return of the quantile temperature-sorted portfolios as the first element of the state vector in a VAR(1) and sequentially introduce predictive variables: the market risk premium (Mkt_RF), the value spread (VS), defined as the log book-to-market difference between small-value and small-growth stocks, the cyclically adjusted price-to-earnings ratio ($CAPE$), and the term spread ($TERM$), the yield difference between 10-year and 2-year Treasury bonds. In a final specification, we also add the innovations in the WSJ climate–change news index Engle et al. (2020) to allow for a climate–driven discount–rate channel. This iterative approach allows us to assess whether the prominence of cash–flow news is a byproduct of the chosen information (Chen and Zhao, 2009) or a feature of returns associated with TAV

Table 5 reports the variance decomposition results alongside the predictive power of the state variables. We find that the forecasting regressions for the temperature L/S portfolio exhibit low explanatory power across all specifications, with R^2 values below 3.0%. As noted by Chen and Zhao (2009), when expected returns exhibit minimal time variation, the VAR decomposition mechanically attributes the majority of unexpected return volatility to the cash–flow component. Consistent with this mechanism, we find that the variance of cash–flow news is an order of magnitude larger than that of discount–rate news across all six information sets. As reported in Table 5, cash-flow news accounts for the dominant share of the variance of unexpected L/S returns. Discount-rate news is near zero in the baseline specifications and at most about one-quarter of the variance of return innovations in Panel B. Iteratively adding each predictor increases the level of discount–rate variance, but its share of total variance remains small. These results indicate that return variation associated with TAV is driven primarily by contemporaneous revisions to firm fundamentals. This pattern is consistent with investors updating valuations when weather shocks materialize, rather than through gradual revisions in expected returns.

These results are logical in that weather shocks should not be predicted by macro-finance variables like CAPE or interest rates and are consistent with the broader anomaly literature. Lochstoer and Tetlock (2020) show that for standard long–short anomaly portfolios, cash–flow news typically explains 64–80% of return variance, while discount–rate news accounts for 7–14%. In our setting, the return innovations associated with TAV are likewise dominated by the cash-flow component, with a modest contribution from time–varying discount rates. This dominance of cash flow news aligns with the evidence that abnormal temperature variability coincides with deterioration in operating performance, consistent with investors pricing the material impact of temperature shocks on firm performance. The limited role of discount rate news is consistent with TAV operating as a source of realized shocks, where price adjustments primarily reflect contemporaneous fundamental effects.

4.3.2 Profitability

In this section, we corroborate the return-based evidence by examining firm-level operating performance. We leverage the plausibly exogenous geographic and time-series variation of TAV to investigate whether revenues-to-assets and profitability (income before extraordinary items scaled by total assets), varies with TAV. We disaggregate these cash flow effects across industries as some may be more responsive to temperature changes than others (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Lee and Zheng, 2025), while certain sectors may even gain from operating in more volatile temperature conditions.[11]

We consider the following specification:

$$\frac{y_{i,s,t}}{Assets_{i,s,t-1}} = \alpha + \beta_1 TAV_{s,t} + \delta' D_{i,t-1} + \gamma_{i,t} + \epsilon_{i,s,t}, \tag{5}$$

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 we multiply by 100 to aid interpretability. Here $TAV_{s,t}$ denotes abnormal temperature variability realized in the same quarter. Firm-level controls, $D_{i,t-1}$, lagged by one quarter, include the log of total assets, the log of book-to-market equity, and the log of plant, property,

[11] Empirical work by Zachariadis and Pashourtidou (2007) and Chang et al. (2016) support this notion, identifying scenarios where atypical temperature patterns can create opportunities rather than challenges.

and equipment over assets, as well as leverage, Tobin's Q, and return on assets. All firm controls are lagged to avoid contamination from contemporaneous temperature shocks. $\gamma_{i,t}$ represents firm-by-year fixed effects such that identification comes from within-firm, within-year variation in quarterly temperature shocks. These fixed effects absorb unobservable firm characteristics and slow-moving adaptation responses, such as investments in climate-resilient infrastructure or operational adjustments.[12]

Table 6 details our findings on firm revenues, starting with the full sample in the first column. An increase in TAV is associated with significantly lower revenues—consistent with the prior cross-sectional return analysis. Specifically, a one standard deviation rise in TAV is associated with a 0.086 percentage point reduction in the ratio within a single quarter. This quarterly effect is economically comparable, though not directly comparable in design, to Pankratz et al. (2023), who find that a similar increase in hot days diminishes the ratio by 0.143% over a year for non-US headquartered firms. In monetary terms, this quarterly impact corresponds to a revenue loss of approximately $385,000 for a firm with the sample's average assets ($445 million).

Before turning to the industry-specific results, we analyze the effects of TAV on profitability, which captures both revenue fluctuations and corresponding adjustments in operating costs. The first column of Table 7 illustrates that a one standard deviation increase in TAV is related to a 0.027% reduction in the profitability ratio over a quarter. Expressed in dollar terms, the effect size suggests a $122,000 decrease in profitability. The larger dollar fall in revenue indicates that managers adjust costs contemporaneously to partially offset revenue losses and stabilize profitability (Bloom, 2014). This aligns with models of expected behavior, where firms respond to uncertainty or negative shocks with caution—postponing investments, cutting discretionary spending, and reducing costs (Bloom, 2014).

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 Business Equipment, Construction, Manufacturing, Money (finance and insurance), Consumer Non-

[12]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.

Durables, and Retail Shops. Industries such as Business Equipment and Manufacturing are capital-intensive and especially vulnerable to supply chain disruptions. The larger decline in revenues relative to profitability suggests that temperature disruptions directly reduce production and sales volumes; however, firms partially offset shocks by cutting costs or adjusting variable inputs. In contrast, the larger effect on profitability relative to revenues in the construction sector reflects that firms must absorb extra costs, such as higher labor expenses from delays, that cannot be fully passed on to consumers.

For Non-Durables and Retail Shops, both revenue and profitability show negative sensitivity to abnormal temperature variability. The business models in these industries rely on high sales volume with low margins, and adverse weather can directly reduce consumer demand and alter purchasing patterns, resulting in lower sales (Roth Tran, 2023; Lee and Zheng, 2025). 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 (Columns (9)), more acute temperature variations may be associated with more frequent and severe climate hazards and disasters, potentially increasing insurance claims unpredictably.[13] The increased financial burden from these payouts can strain insurance firms' resources, thereby exerting downward pressure on profitability and returns.[14]

In contrast, we observe a positive and significant relationship between TAV and revenues for Utilities, though this effect does not extend to profitability. The institutional features of Utilities firms are unique due to their regulatory constraints. Firms charge a fixed rate per unit of energy, approved periodically by public utility commissions based on projected usage and costs. This rate structure implies that total energy demand may rise during periods of heightened temperature extremes, boosting revenues,[15] but that unexpected operational costs may also increase, and these cost increases may not be fully recoverable through contemporaneous price adjustments.

[13] In a June 2025 note, Swiss Re Institute warns that extreme heat heightens property losses, disrupts infrastructure, stresses healthcare systems, and raises liability risks, posing a threat to insurer balance sheets.

[14] A recent Financial Times article supports this claim, indicating that US home insurers have incurred substantial losses due to extreme weather conditions—see the FT article 'US home insurers suffer worst loss this century', July 2024.

[15] This observation is supported by prior work documenting the strong sensitivity of electricity demand to temperature fluctuations (Zachariadis and Pashourtidou (2007) and Chang et al. (2016)).

We also detect a positive relationship between both revenue and income and TAV in the Energy sector (oil, gas, and coal extraction). This is likely driven by increased energy demand and potential supply disruptions caused by abnormal temperatures. Xu et al. (2023) find similar effects on oil prices, which are likely to be reflected in the income of firms engaged in energy extraction.

These cash-flow effects extend Choi et al. (2020), who show that equities of carbon-intensive firms underperform during periods of higher-than-normal temperatures. They attribute this underperformance to an attention-driven discount rate channel, explicitly finding no evidence that the price impact is driven by changes in firm fundamentals. We instead demonstrate that equity returns respond to realized abnormal temperature variability through material, operational disruptions. Our evidence suggests that markets are reacting to the physical consequences of unexpected local weather shocks as they occur, rather than updating their pricing of ex-ante transition risk.

5 Cash-flow transmission and informational mechanisms

This section investigates the economic mechanisms through which abnormal temperature variability generates variation in firm cash flows, driving the documented return spread. We first examine the real channels, focusing on how realized temperature shocks affect household demand and labor supply, which in turn impact firm revenues and profitability. Next, we assess how market participants process these effects, examining shifts in investor and analyst attention. Finally, we study the roles of belief heterogeneity and valuation uncertainty in modulating how these effects are incorporated into asset prices.

5.1 Economic channels

On the demand side, we use the Consumer Expenditure Survey to examine how consumer expenditure patterns responds to TAV. On the supply side, we analyze labor responses using the American Time Use Survey. We find that higher TAV is associated with lower household spending, with economically meaningful heterogeneity across consumption categories. At the same time, industries exposed to greater temperature variability consistently log fewer hours

worked, indicating abnormal temperature fluctuations impair labor input and contribute to higher operating costs and weaker profitability.

5.1.1 Consumer expenditure

We examine how abnormal temperature variability influences household spending across different consumption categories.[16] To the extent that abnormal temperature variability depresses consumption, firms operating in exposed sectors face immediate revenue headwinds, providing a direct mechanism through which high-TAV exposure translates into weaker cash flows and lower equity valuations.

We draw on data from the Consumer Expenditure Survey (CEX) from 1994 to 2019, which allows us to observe household-level spending responses to realized temperature variability. The CEX is a rotating panel of households representative of the non-institutionalized US population and provides detailed information on consumption expenditures alongside demographic characteristics such as household members, age, education, and family income. Specifically, we use the FMLI files, which report households characteristics such as size and state of residence, and include aggregate expenditure variables across categories such as apparel and electricity. Each household is interviewed at three-month intervals, with each interview detailing expenditures incurred over the preceding three months. This rolling interview structure allows us to align household spending with contemporaneous realizations of abnormal temperature variability over the same horizon, which is well suited to capturing short-run demand responses.

Our sample construction excludes households residing in student housing and those with household members younger than 21 or older than 85 years. These restrictions improve comparability across households and reduce noise from life-cycle-specific consumption dynamics, yielding approximately 20,775 household interviews per annum across 43 states, though this number declined to 12,975 interviews in 2019. Expenditures for the three months preceding each interview are constructed by aggregating current-quarter and past-quarter expenditure data across various categories—non-durables, durables, utilities, electricity, healthcare, enter-

[16]Literature has investigated the effects of temperature on household consumption (Roth Tran, 2023; Lee and Zheng, 2025) and electricity demand (Zachariadis and Pashourtidou, 2007; Chang et al., 2016), documenting a moderate impact of extreme temperatures on consumer spending and electricity demand.

tainment, and apparel—as detailed in Panel E of Table A.1 in the Appendix. These expenditure categories map naturally into revenue exposure for different sectors of the economy and serve as the primary dependent variables in our empirical tests, following the specification:

$$Expenditure_{h,s,t} = \alpha + \beta_1 TAV_{s,t} + \delta' D_{h,t} + \theta' Q_{s,t} + \rho_t + \gamma_{s,y} + \epsilon_{h,s,t}, \tag{6}$$

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. $TAV_{s,t}$ measures abnormal temperature variability over the same three-month period in state s. The vector D includes household-specific continuous covariates, detailed in Table **??**. The vector Q denotes year-over-year changes in state-level covariates: the consumer price index, house price index, personal income, and unemployment rate. We additionally control for marital status, education level, race, urban or rural status, and housing tenure. To mitigate the influence of outliers, all control and expenditure variables are winsorized at the 1% level. Year by quarter fixed effects, ρ_t, absorb aggregate seasonality and macroeconomic shocks while state by year fixed effects, $\gamma_{s,y}$, control for unobserved state-level trends. Identification therefore comes from within-state variation over time in abnormal temperature variability, with standard errors clustered at the state level. If an interview is conducted in January or February, we set the year fixed effect to correspond to the previous year.

Table 8 presents the results from the panel regressions for each expenditure category. The first column reveals that a one-standard-deviation increase in TAV is associated with a 0.31% reduction in total household expenditure. For scale, an additional household member is associated with a 2.7% increase in expenditures over the prior three months. To illustrate economic magnitude, consider Texas: for the average household with annual expenditures of roughly $34,000, a one-standard-deviation increase in TAV implies a reduction in spending of approximately $105 per year. For the 42,248 surveyed households in Texas, this corresponds to an aggregate decline of over $4.4 million per year. Extrapolating to the nearly 10 million households in Texas in 2019, this implies an annual expenditure reduction exceeding $1.05 billion under comparable deviations in abnormal temperature variability.

Consistent with the heterogeneous firm-level cash-flow responses documented in Section

4, we find substantial variation in the sensitivity of household spending to realized TAV across categories. TAV is positively associated with electricity spending, paralleling the positive effect of TAV on profitability observed in our industry-level analysis. This pattern suggests that abnormal temperature variability raises household demand for heating and cooling, increasing revenues for utility providers. In contrast, Table 8 reports a negative relationship between TAV and discretionary categories—including non-durables, durables, and apparel—consistent with the broad-based revenue declines documented in Section 4.3.

These findings substantiate a demand-side cash-flow transmission channel through which abnormal temperature variability affects household spending. The resulting heterogeneity across expenditure categories mirrors the firm-level differences in revenue sensitivity and performance. Our results complement Addoum et al. (2023), who document declines in foot traffic in consumer-facing sectors, and are consistent with Lee and Zheng (2025), who show that extreme temperatures reduce weekly household retail consumption.

5.1.2 Labor hours worked

Prior work documents that extreme temperature conditions can reduce labor supply, particularly in physically exposed occupations (Graff Zivin and Neidell, 2014; Somanathan et al., 2021). Reductions in labor input can raise production costs through delays, inefficiencies, and costly operational adjustments, providing a supply-side channel through which adverse weather conditions translate into weaker firm cash flows. Here, we examine whether abnormal temperature variability, capturing temperature shocks, also affects labor supply. Specifically, we study how TAV relates to hours worked, shedding light on workers' responsiveness to more volatile temperature patterns.

We use the American Time Use Survey Data, a nationally representative cross-sectional survey that documents how Americans aged 15 and over allocate their from 2003 to 2019. Respondents complete a detailed 24-hour diary on the day preceding the interview, including the type, locations, and duration (to the minute) of each activity. This measurement allows us to capture short-run labor supply responses to realized temperature variability. Following Graff Zivin and Neidell (2014), we construct a measure of total hours worked based on respondents' reported activities during that day.

To account for differences in exposure to temperature conditions across occupations, we adopt the classification used in Graff Zivin and Neidell (2014) to distinguish between industries with higher and lower physical exposure to weather conditions. High-risk workers are defined as those employed in agriculture, forestry, fishing, hunting, mining, construction, manufacturing, transport and utilities sectors (comprising approximately 23% of the data), where outdoor work or physically intensive tasks are more prevalent. The remaining industries—including wholesale and retail trade, information, professional and business services, educational and health services, leisure and hospitality, other services, and public administration—are categorized as low risk (76% of the sample). We create an indicator variable equal to 1 for respondents employed in a "high-risk" industry and 0 otherwise.

We regress the minutes worked during the day prior to the interview ($Work$), focusing on whether labor supply in more temperature-exposed industries responds more strongly to abnormal temperature variability, through the interaction between state-level TAV and the high-risk industry indicator as follows:

$$\begin{aligned} Work_{h,s,i,t} = \alpha + \beta_1 TAVs^{[t-15,t]} + \beta_2\big(TAV_s^{[t-15,t]} \times HighRisk_i\big) + \\ \delta' X_h \ + \theta' Z_{s,t} + \rho_{s,q} + \gamma_{i,y} + \varepsilon_{h,s,i,t}, \end{aligned} \tag{7}$$

where $Work$ is the minutes worked on the prior day for respondent h, in state s, in industry i, and on day t. $TAV_{s,t}$ measures abnormal temperature variability over the 15 days ending at t, capturing short-run fluctuations preceding the interview. $HighRisk_i$ is an indicator for high-risk industries. X includes variables for age, marital status, education, race, household income, number of children, sex, and self-employment. Z includes state-level climate variables calculated over the same window as TAV: average temperature TA, average precipitation, and a wildfire index. Z also includes the year-over-year growth in the house price index, personal income, and the unemployment rate. We include state-by-season fixed effects $\rho_{s,q}$ and industry-by-year fixed effects $\gamma_{i,y}$, absorbing regional seasonality and industry-specific trends, and cluster standard errors by state.

Table 9 reports that workers in high-risk industries log approximately 2.7 fewer minutes of work for each one-unit increase in TAV relative to their low-risk counterparts. This finding echoes the results of Neidell et al. (2021), who report that high-risk workers reduce labor

supply by about 2.6 minutes for each degree above 90°F. A key distinction, however, is that our estimates are stable across the business cycle, suggesting that the effects of abnormal temperature variability on labor supply reflect persistent productivity disruptions rather than transitory cyclical adjustments.

5.2 Attention, beliefs, and informational frictions

Beyond its tangible effects on firm fundamentals, abnormal temperature variability likely serves as an informational signal, shaping how market participants process climate-related risks. Because TAV reflects idiosyncratic and transitory temperature shocks, it may act as a cue that heightens attention to climate risk among investors, analysts, and the broader public. This dynamic aligns with models of rational inattention, in which agents allocate limited attention only upon observing salient shocks, rather than continuously monitoring climate risk. Empirically, this mechanism implies episodic spikes in climate-related attention following realizations of abnormal temperature variability.

5.2.1 Attention

We consider three complementary measures of attention: (i) retail investors attention, proxied by Google search activity related to climate change; (ii) media attention, captured by the Wall Street Journal climate news index; and (iii) analyst attention, measured by the share of firm earnings calls devoted to climate-related topics. Together, these indices measure how limited information-processing capacity is reallocated across market participants in response to salient temperature shocks, consistent with a rational-inattention setting.

We begin by using state-level Google Trends data to proxy for aggregate public attention to climate change, following Da et al. (2011), and Choi et al. (2020). Specifically, we focus on innovations in Google search interest for the term "climate change", obtained as residuals from an AR(1) model estimated at the state level. By filtering out persistent trends in search activity, these innovations capture unexpected shifts in attention.

We regress these innovations in public attention on TAV, testing whether abnormal temperature variability triggers climate-related attention, while controlling for other climate-related risks (average temperature anomalies, precipitation, and wildfires), local economic

conditions, and state and year fixed effects:

$$SVI_{s,t} = \alpha + \beta_1 TAV_{s,t} + \delta' X_{s,t} + \rho_{s,t} + \epsilon_{s,t}. \tag{8}$$

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.

As shown in Table 10, we find a positive and statistically significant association between TAV and unexpected state-level climate-related search activity. This result indicates that realizations of abnormal temperature variability are followed by discrete increases in public attention to climate change, and it remains robust across alternative specifications and fixed effects. The evidence supports the interpretation of TAV as a salient informational trigger, consistent with findings in (Choi et al., 2020).

We next assess whether these attention responses extend beyond local public interest to national media coverage, examining whether abnormal temperature variability influences aggregate media attention to climate change. Specifically, we use the climate news index developed by Engle et al. (2020), which tracks the frequency of climate-related terms in Wall Street Journal articles. Because national media coverage shapes investor narratives and frames perceptions of climate risk, this index provides a proxy for shifts in aggregate discourse beyond local weather realizations. To isolate unexpected shifts in climate news coverage, we apply the same AR(1) residual approach and regress the innovations on a population-weighted, national-level TAV index:

$$WSJ_t = \alpha + \beta_1 TAV_t + \delta' X_{s,t} + \rho_t + \epsilon_t, \tag{9}$$

where $X_{s,t}$ includes national controls (e.g., precipitation, wildfires, and temperature anomalies), and ρ_t captures time fixed effects.[17]

Across most specifications in Table 11, we find a statistically significant positive relationship between TAV and innovations in national climate news coverage. This evidence suggests that periods of abnormal temperature variability coincide with heightened media focus on climate change, reinforcing the interpretation of TAV as a salient trigger for public

[17]Details for calculating a population-weighted *TAV* can be found in Appendix B.1.2.

climate related discourse.

To assess whether sophisticated market participants respond similarly, we turn to earnings conference calls. Specifically, we use the measure $CCExposure$ from Sautner et al. (2023), which quantifies the share of earnings call content devoted to climate-related topics. This measure reflects the degree to which participants—management and sell-side analysts—perceive climate risk as relevant to firm performance.[18] We estimate the following model:

$$CCExposure_{i,t} = \alpha + \beta_1 TAV_{s,t} + \beta_2 WSJ_t + \delta' D_{i,t-1} + \gamma_{ind} + \epsilon_{i,s,t}. \tag{10}$$

where firm i is headquartered in state s and observed at year t. The vector of firm-level controls $D_{i,t-1}$ includes the log of total assets, leverage, log book-to-market equity, Tobin's Q, return-on-assets, and the log of plant, property, and equipment over assets. We lag these variables by one year to mitigate simultaneity concerns, as current values may be affected by contemporaneous temperature variability. We control for industry fixed effects (γ_{ind}) and include innovations (AR(1) residuals) in the WSJ climate news index (WSJ_t) to separate firm-level responses to realized TAV from aggregate climate attention that may concurrently shift climate-related discussion in earnings calls.

Table 12 shows a significant positive association between TAV and climate-related analyst attention. This relationship is not subsumed by national media coverage, indicating that realized abnormal temperature variability conveys incremental, firm-relevant information beyond aggregate climate news. While other climate-related indicators have muted explanatory power, TAV is a consistent driver of climate-related discussion during earnings calls, suggesting that analysts interpret temperature variability as salient. Taken together, these results establish abnormal temperature variability as a salient informational signal, heightening attention to climate risk among the public, the media, and professional analysts.

[18] 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.

5.2.2 Beliefs

Attention is necessary but not sufficient for prices to fully reflect climate risk. While our attention indices measure salience and information acquisition, asset prices ultimately depend on whether investors update their beliefs about the economic relevance of climate-related shocks. We therefore ask whether TAV shifts climate beliefs, and along which margins. In particular, we distinguish between general beliefs about whether climate change is occurring and beliefs about personal exposure and harm. The latter provides a closer proxy for perceived near-term economic relevance, without requiring respondents to revise their broader views on climate change. Salient temperature shocks can prompt agents to reweight previously neglected risks (Gennaioli et al., 2015), but belief updating is uneven and shaped by prior views (Deryugina, 2013), giving rise to persistent belief heterogeneity. Consistent with this, individuals often interpret climate and disaster events through the lens of their ideological and personal priors, which can reinforce rather than attenuate disagreements about climate risk (Bakkensen and Barrage, 2022; Bernstein et al., 2019).[19]

To study belief dynamics, we combine our temperature data with state-level climate risk perception data from the Yale Program on Climate Change Communication (YPCCC) (Marlon et al., 2022). The YPCCC survey indicates that between 2010 and 2019, beliefs about the existence of global warming were widespread, while perceptions of personal exposure and harm were substantially less common. We use state-by-year data from 2010 to 2019 to measure the percentage of respondents who answered "Yes" to three key survey 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.

To measure unexpected changes in beliefs, we estimate AR(1) models for each series at the state level, filtering out slow-moving trends and persistence in attitudes. We then regress these innovations on TAV, controlling for state-level economic conditions and other physical risk variables. Year and state fixed effects absorb common time shocks and regional

[19]For instance, commentary on flash floods in Texas in July 2025 noted that such events are likely to shape public attitudes toward climate change, but that the direction and strength of this effect vary substantially with individuals' prior beliefs. Link to the FT article: "Does catastrophe affect how we think about climate change?", July 2025.

differences, isolating within-state variation in unexpected belief changes. In addition, we proxy local attention using innovations in state-level Google search intensity for the topic "Climate Change", allowing us to distinguish belief updating from changes in salience alone.

Table 15 presents the regression results for belief innovations. Columns (1)–(4) report estimates for question (a), columns (5)–(8) for question (b), and columns (9)–(12) for question (c). We find no significant relationship between TAV and changes in the share of respondents who believe that global warming is happening. This null result suggests that views on the existence of climate change are entrenched, making it inelastic to short-term temperature fluctuations. TAV, however, increases perceptions of personal exposure to climate change. Column (5) shows that a one-standard-deviation increase in TAV is associated with a 0.29 percentage point rise in the share of respondents reporting that they have personally experienced the effects of global warming. Similarly, column (9) shows a positive association—0.14 percentage points—with the belief that global warming will harm people in the US. These results suggest that respondents interpret abnormal temperature variability as tangible evidence of climate-related impacts, shifting perceptions of exposure and damages that are a natural margin through which weather realizations can become economically salient, without requiring belief updating about whether climate change is occurring. These relationships remain robust after controlling for additional physical risks, economic conditions, and state and year fixed effects. Innovations in climate-related search activity are positively associated with all belief measures, indicating that greater attention coincides with stronger beliefs, but does not mechanically translate into belief updating along economically relevant dimensions.

The findings that TAV shifts perceptions of personal exposure and expected harm, rather than baseline beliefs about whether warming is occurring, highlights an informational friction in belief updating. Differences in how investors interpret abnormal temperature variability imply uneven updating of of cash-flow expectations, which can slow the incorporation of TAV-related information into prices and contributing to the observed dispersion in valuations. Consistent with rational inattention, salient TAV shocks may attract attention without generating uniform revisions in beliefs about economically relevant risks.

5.3 Uncertainty and disagreement frictions

Although investors appear attentive to temperature variability when it occurs—evidenced by the contemporaneous spikes in attention and return responses—our analysis of beliefs suggests that behavioral frictions limit the processing of these signals. Abnormal temperature variability can affect firms through multiple channels—damaging physical capital, disrupting operations, and altering local demand for exposed firms—making its ultimate impact on cash flows uncertain (Kruttli et al., 2025). This valuation uncertainty complicates the translation of realized temperature shocks into prices, contributing to disagreement and the persistence of the observed return spread.

We test whether TAV is associated with firm-level uncertainty using two standard proxies: (i) idiosyncratic return volatility and (ii) dispersion in analysts' earnings forecasts. If abnormal temperature variability increases uncertainty about future cash flows, firms experiencing higher TAV should exhibit greater firm-specific return volatility and wider disagreement among market participants.

5.3.1 Idiosyncratic return volatility

We estimate the relationship between TAV and idiosyncratic firm-level return volatility using Fama-MacBeth regressions. For each firm and month, we compute idiosyncratic return volatility as the standard deviation of the residuals from a regression of daily log stock returns on the Fama-French three-factor model, isolating the component of return variability not explained by common risk factors.[20]

Control variables largely mirror those used in Section 4.2, with two key additions: lagged return volatility and changes in the VIX index from the Chicago Board Options Exchange (Ang et al., 2006). Lagged volatility captures persistence in firm-specific risk, while changes in the VIX proxy for time-varying aggregate uncertainty (Ang et al., 2009). We also control for contemporaneous quarterly dispersion in analyst forecasts, following (Diether et al., 2002), to separate volatility arising from disagreement among analysts from volatility reflecting broader fundamental uncertainty induced by temperature variability. Analyst forecast

[20]Using log returns helps mitigate the positive skewness in raw returns, which could otherwise introduce a spurious correlation between realized mean returns and realized variance (Ang et al., 2009).

dispersion is measured as the natural logarithm of the standard deviation of analyst earnings forecasts, sourced from I/B/E/S. While informative, this control introduces potential endogeneity concerns, as TAV may influence both analyst forecast dispersion and, through it, return volatility. Moreover, incorporating analyst forecast data limits the sample to larger firms, which typically exhibit lower return volatility due to broader analyst coverage. This may bias results toward more conservative estimates of the effect of TAV.

Table 13 reports the results of the Fama-MacBeth regressions. The positive and statistically significant coefficients on abnormal temperature variability in the first row indicate that, within a given month, firms experiencing greater temperature variability also exhibit higher return volatility. This relationship survives after controlling for lagged return volatility, changes in the VIX index, and lagged returns. A one-standard deviation increase in TAV raises the natural log of return volatility by 0.115, corresponding to an approximate 12.2% increase in firm-specific return volatility. Given that the standard deviation of log return volatility in the sample is 0.650, this implies that a TAV shock accounts for more than one-tenth of the cross-sectional variation in firm-level return volatility.

Abnormal temperature variability thus appears to drive firm-specific return fluctuations and contribute to valuation noise, even after controlling for other physical risk indicators such as temperature anomalies, precipitation, and wildfires (column (5)). The relationship also holds when accounting for climate-related news shocks measured by the innovation of the Wall Street Journal climate change news index (column (6)), and when controlling for potential disagreement among analysts, proxied by the dispersion of earnings forecasts (column (7)).[21]

5.3.2 Analyst forecasts

We next examine the relationship between temperature variability and market uncertainty through analyst earnings forecasts, focusing on disagreement and forecast errors as indicators of uncertainty about firm fundamentals. Following Diether et al. (2002), we use the dispersion in analysts' earnings-per-share (EPS) forecasts as a proxy for disagreement among informed

[21]Column (5) shows that, aside from abnormal precipitation, other physical risk indicators are not significantly linked to return volatility. Column (6) finds that unexpected shifts in the Wall Street Journal climate change news index are positively associated with volatility, and column (7) shows that greater analyst forecast dispersion corresponds to about a 4% increase in volatility.

market participants—differences of opinion that reflect uncertainty about firm fundamentals. Analyst forecast dispersion is informative because it reveals whether abnormal temperature variability widens differences in expectations among sophisticated market participants. We also estimate the effect of TAV on quarterly earnings surprises, scaled by the prior quarter's stock price. The deviation between forecast and realized earnings further indicates whether these investors can accurately anticipate the financial impact of temperature variability.

To examine whether TAV widens disagreement among analysts and leads to systematic forecast errors, we merge quarterly firm-level EPS forecast data from I/B/E/S with performance data from Compustat, as described in Section 4.3. We estimate the following:

$$\mathrm{Y}_{i,t} = \alpha + \beta_1 TAV_{s,t} + \beta_2 \mathrm{Analysts}_{i,t} + \delta' X_{i,t-1} + \theta' D_{s,t} + \gamma_{i,year} + \varepsilon_{it} \tag{11}$$

where Y is either the log of the standard deviation of analyst EPS forecasts or the quarterly earnings surprise divided by the prior quarter's stock price, constructed for firm i in quarter t. Control variables $X_{i,t-1}$, lagged by one quarter, include the log of total assets, the log of book-to-market equity, and the log of plant, property, and equipment over assets, as well as leverage, Tobin's Q, and return on assets. $D_{s,t}$ includes state-level indicators, like house price index, personal income, and unemployment rate, expressed as year-over-year growth. $\mathrm{Analysts}_{i,t}$ is the number of analysts covering the firm. γ denotes firm-by-year fixed effects.

The first four columns of Table 14 report results using the standard deviation of analyst EPS forecasts as the dependent variable. Across these columns, TAV is positively associated with greater dispersion in analyst forecasts, indicating increased disagreement during periods of abnormal temperature variability. This relationship weakens once firm-by-year fixed effects are included, suggesting that the association is driven more by cross-sectional differences in exposure than by within-firm time variation. Consistent with this interpretation, increases in TAV for a given firm are linked to contemporaneous rises in analyst forecast dispersion relative to the firm's own historical average. In column (1), a one-standard deviation increase in TAV raises forecast dispersion by about 2%, indicating that professional expectations are modestly responsive to temperature-related exposure.

The last four columns of Table 14 use the quarterly earnings surprise, scaled by lagged

stock price and multiplied by 100, as the dependent variable. Column (5) shows that a one-standard deviation increase in TAV is associated with a 0.03-point decline in the scaled earnings surprise—roughly 5.2% of the variable's mean. Negative EPS surprises imply that, on average, realized firm performance falls short of expectations. This pattern reveals that analysts only partially anticipate the cash-flow implications of abnormal temperature variability. These findings are consistent with Pankratz et al. (2023), who document that greater heat exposure is linked to more negative revenue and income surprises.

The evidence in this section supports the view that TAV raises valuation uncertainty and contributes to disagreement among informed investors. While investors and analysts are attentive to temperature variability—coinciding with the initial return reaction—uncertainty remains regarding its ultimate effects on firms. In turn, this uncertainty can sustain dispersion in valuations and contribute to the persistence of the return spread. This suggests that some investors struggle to interpret the impact of abnormal temperature variability shocks, leading to greater uncertainty and analysts' underestimation of the effects of TAV.

6 Conclusion

Climate change is increasing the frequency and intensity of short-run temperature shocks, yet it remains unclear whether and how equity markets incorporate their implications when they occur. While prior work documents strong effects of shifts in mean conditions and extreme-temperature days on economic activity and expectations, contemporaneous equity returns respond only weakly to the same realizations. To shed light on this puzzle, we construct a novel measure of abnormal temperature variability that benchmarks realized intra-period dispersion against rolling, location- and season-specific baselines, thereby focusing on unexpected, short-lived fluctuations that rotate across regions. Firms whose realized exposure coincides with elevated temperature variability earn lower contemporaneous returns, while episodic attention and incomplete belief updating generate uncertainty that slows incorporation into prices.

Consistent with the idiosyncratic, rotating nature of abnormal temperature variability, the return response manifests contemporaneously as cash-flow news rather than discount-

rate news, indicating that markets treat these shocks as revisions to expected fundamentals rather than compensation for systematic climate and temperature risk. We corroborate this interpretation with evidence on real economic outcomes. Elevated temperature variability reduces firm revenues and profitability by depressing household spending and hours worked, with particularly strong effects in consumer-facing and labor-intensive sectors.

However, our empirical evidence indicates that the market's reaction to this information is subject to frictions. Although abnormal temperature variability attracts attention, realized exposure is episodic even though exposure is widespread, making cash-flow consequences difficult to anticipate and costly to process continuously. Consistent with this interpretation, we document heightened firm-specific volatility, greater analyst forecast dispersion, and systematic earnings surprises following periods of elevated temperature variability, indicating substantial disagreement about firm-level impacts. As a result, investors rationally allocate limited attention ex-ante, and prices adjust mainly on impact through cash-flow news rather than via a persistent climate factor, consistent with rational inattention.

While rational inattention is consistent with our evidence, we cannot rule out an information-quality channel. Local weather realizations may be noisy, measured with error, or hard to map into firm-level exposure in real time, limiting their ex ante predictive content for cash flows and dampening anticipatory pricing even in the absence of attention constraints. An important direction for future work is to disentangle these channels by exploiting shocks to information quality that increase signal precision without altering underlying temperature risk.

These findings carry implications for investors, firms, and regulators. For investors, TAV represents a source of exposure that could be systematically exploited in cross-sectional strategies. For firms, exposure to abnormal temperature variability underscores the importance of operational resilience and adaptation strategies. For regulators and standard-setters, TAV offers a scalable metric for assessing physical climate risk exposure, derived entirely from publicly available data without reliance on self-reported firm information. Practical applications could include the construction of a temperature-resilient portfolio using TAV-based sorting, or the integration of TAV in standardized climate-risk reporting frameworks.

References

Acharya, V. V., T. Johnson, S. Sundaresan, and T. Tomunen (2022). Is physical climate risk priced? evidence from regional variation in exposure to heat stress. Technical report, National Bureau of Economic Research.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2020). Temperature shocks and establishment sales. *The Review of Financial Studies 33*(3), 1331–1366.

Addoum, J. M., D. T. Ng, and A. Ortiz-Bobea (2023). Temperature shocks and industry earnings news. *Journal of Financial Economics 150*(1), 1–45.

Akerlof, K., E. W. Maibach, D. Fitzgerald, A. Y. Cedeno, and A. Neuman (2013). Do people "personally experience" global warming, and if so how, and does it matter? *Global Environmental Change 23*(1), 81–91.

Alekseev, G., S. Giglio, Q. Maingi, J. Selgrad, and J. Stroebel (2022). A quantity-based approach to constructing climate risk hedge portfolios. *Available at SSRN 4283192*.

Allan, R. P. and B. J. Soden (2008). Atmospheric warming and the amplification of precipitation extremes. *Science 321*(5895), 1481–1484.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006). The cross-section of volatility and expected returns. *The Journal of Finance 61*(1), 259–299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009). High idiosyncratic volatility and low returns: International and further us evidence. *Journal of Financial Economics 91*(1), 1–23.

Auffhammer, M., S. M. Hsiang, W. Schlenker, and A. Sobel (2013). Using weather data and climate model output in economic analyses of climate change. *Review of Environmental Economics and Policy*.

Bae, J. W., Y. Jeon, S. Szaura, and V. Zurita (2023). Blame it on the weather: Market-implied weather volatility and firm performance.

Bakkensen, L. A. and L. Barrage (2022). Going underwater? Flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies 35*(8), 3666–3709.

Bansal, R., D. Kiku, and M. Ochoa (2019). Climate change risk.

Benjamini, Y. and D. Yekutieli (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of Statistics*, 1165–1188.

Bernile, G., A. Kumar, and J. Sulaeman (2015). Home away from home: Geography of information and local investors. *The Review of Financial Studies 28*(7), 2009–2049.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics 134*(2), 253–272.

Bettarelli, L., D. Furceri, M. Ganslmeier, and M. T. Schiffbauer (2025). The economic costs of temperature uncertainty. IMF Working Paper WP/25/26, International Monetary Fund.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives 28*(2), 153–176.

Burke, M. and V. Tanutama (2019). Climatic constraints on aggregate economic output. Technical Report 25779, National Bureau of Economic Research.

Campbell, J. Y. (1991). A variance decomposition for stock returns. *The economic journal 101*(405), 157–179.

Chan, L. K., N. Jegadeesh, and J. Lakonishok (1996). Momentum strategies. *The Journal of Finance 51*(5), 1681–1713.

Chang, Y., C. S. Kim, J. I. Miller, J. Y. Park, and S. Park (2016). A new approach to modeling the effects of temperature fluctuations on monthly electricity demand. *Energy Economics 60*, 206–216.

Chen, A. Y. and T. Zimmermann (2022). Open source cross-sectional asset pricing. *Critical Finance Review 27*(2), 207–264.

Chen, L. and X. Zhao (2009). Return decomposition. *The Review of Financial Studies 22*(12), 5213–5249.

Choi, D., Z. Gao, and W. Jiang (2020). Attention to global warming. *The Review of Financial Studies 33*(3), 1112–1145.

Conley, T. G. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics 92*(1), 1–45.

Cruz, J.-L. and E. Rossi-Hansberg (2023). The economic geography of global warming. *Review of Economic Studies 91*(2), 899–939.

Cuculiza, C., A. Kumar, W. Xin, and C. Zhang (2025). Temperature sensitivity, mispricing, and predictable returns. *Management Science*.

Da, Z., J. Engelberg, and P. Gao (2011). In search of attention. *The Journal of Finance 66*(5), 1461–1499.

Dell, M., B. F. Jones, and B. A. Olken (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics 4*(3), 66–95.

Dell, M., B. F. Jones, and B. A. Olken (2014). What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature 52*(3), 740–798.

Deryugina, T. (2013). How do people update? the effects of local weather fluctuations on beliefs about global warming. *Climatic Change 118*, 397–416.

Diether, K. B., C. J. Malloy, and A. Scherbina (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance 57*(5), 2113–2141.

Donadelli, M., M. Jüppner, A. Paradiso, and C. Schlag (2019). Temperature volatility risk. *University Ca'Foscari of Venice, Dept. of Economics Research Paper Series No 5*.

Durre, I., M. F. Squires, R. S. Vose, A. Arguez, W. S. Gross, J. J. Rennie, and C. J. Schreck (2022). NOAA's nClimGrid-Daily Version 1: Daily Gridded Temperature and Precipitation for the Contiguous United States Since 1951. NOAA National Centers for Environmental Information.

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020). Hedging climate change news. *The Review of Financial Studies 33*(3), 1184–1216.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*(3), 607–636.

Frazzini, A. and L. H. Pedersen (2014). Betting against beta. *Journal of Financial Economics 111*(1), 1–25.

Garcia, D. and Ø. Norli (2012). Geographic dispersion and stock returns. *Journal of Financial Economics 106*(3), 547–565.

Gennaioli, N., A. Shleifer, and R. Vishny (2015). Neglected risks: The psychology of financial crises. *American Economic Review 105*(5), 310–314.

Graff Zivin, J. and M. Neidell (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics 32*(1), 1–26.

Hansen, J., D. Johnson, A. Lacis, S. Lebedeff, P. Lee, D. Rind, and G. Russell (1981). Climate impact of increasing atmospheric carbon dioxide. *Science 213*(4511), 957–966.

Hansen, J., M. Sato, and R. Ruedy (2012). Perception of climate change. *Proceedings of the National Academy of Sciences 109*(37), E2415–E2423.

Hartzmark, S. M. and D. H. Solomon (2013). The dividend month premium. *Journal of Financial Economics 109*(3), 640–660.

Jones, B., J. Moscona, B. A. Olken, and C. von Dessauer (2026). With or without u? binning bias and the causal effects of temperature extremes. Technical report, National Bureau of Economic Research.

Katz, R. W. and B. G. Brown (1992). Extreme events in a changing climate: variability is more important than averages. *Climatic Change 21*(3), 289–302.

Kelly, D. L., C. D. Kolstad, and G. T. Mitchell (2005). Adjustment costs from environmental change. *Journal of Environmental Economics and Management 50*(3), 468–495.

Kotz, M., L. Wenz, A. Stechemesser, M. Kalkuhl, and A. Levermann (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change 11*(4), 319–325.

Kruttli, M. S., B. R. Tran, and S. W. Watugala (2025). Pricing poseidon: Extreme weather uncertainty and firm return dynamics. *The Journal of Finance 80*(2), 783–832.

Lee, S. and S. Zheng (2025). Extreme temperatures, adaptation capacity, and household retail consumption. *Journal of the Association of Environmental and Resource Economists 12*(2), 427–457.

Linsenmeier, M. (2022). Seasonal temperature variability.

Lochstoer, L. A. and P. C. Tetlock (2020). What drives anomaly returns? *The Journal of Finance 75*(3), 1417–1455.

Marlon, J. R., X. Wang, P. Bergquist, P. D. Howe, A. Leiserowitz, E. Maibach, M. Mildenberger, and S. Rosenthal (2022). Change in US state-level public opinion about climate change: 2008–2020. *Environmental Research Letters 17*(12), 124046.

Neidell, M., J. Graff Zivin, M. Sheahan, J. Willwerth, C. Fant, M. Sarofim, and J. Martinich (2021). Temperature and work: Time allocated to work under varying climate and labor market conditions. *PloS One 16*(8), e0254224.

Pankratz, N., R. Bauer, and J. Derwall (2023). Climate change, firm performance, and investor surprises. *Management Science*.

Pankratz, N. M. and C. M. Schiller (2024). Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies 37*(6), 1729–1777.

Roth Tran, B. (2023). Sellin'in the rain: Weather, climate, and retail sales. *Management Science 69*(12), 7423–7447.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Schlenker, W. and C. A. Taylor (2021). Market expectations of a warming climate. *Journal of Financial Economics*.

Somanathan, E., R. Somanathan, A. Sudarshan, and M. Tewari (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy 129*(6), 1797–1827.

Starr, M. (2000). The effects of weather on retail sales. Finance and economics discussion series, Board of Governors of the Federal Reserve System (U.S.).

Wu, S., M. Luo, G. N.-C. Lau, W. Zhang, L. Wang, Z. Liu, L. Lin, Y. Wang, E. Ge, J. Li, et al. (2025). Rapid flips between warm and cold extremes in a warming world. *Nature Communications 16*(1), 3543.

Xu, Y., D. Duong, and H. Xu (2023). Attention! Predicting crude oil prices from the perspective of extreme weather. *Finance Research Letters 57*, 104190.

Yang, J. and C. Schoder (2025). Impact of temperature uncertainty on firm growth: A grid-level analysis. Policy Research Working Paper 1120, World Bank Group.

Zachariadis, T. and N. Pashourtidou (2007). An empirical analysis of electricity consumption in cyprus. *Energy Economics 29*(2), 183–198.

7 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). We parse the 10-K filings of all listed US companies for each year to identify the number of times the US states 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. Then, we average this for each firm to obtain a metric that we define as the 10-K measure of state operational dispersion.

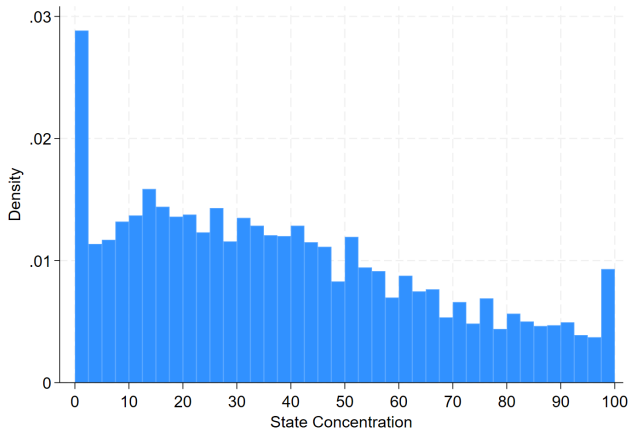


Figure 2: US revenue concentration of firms based on Compustat segments

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.

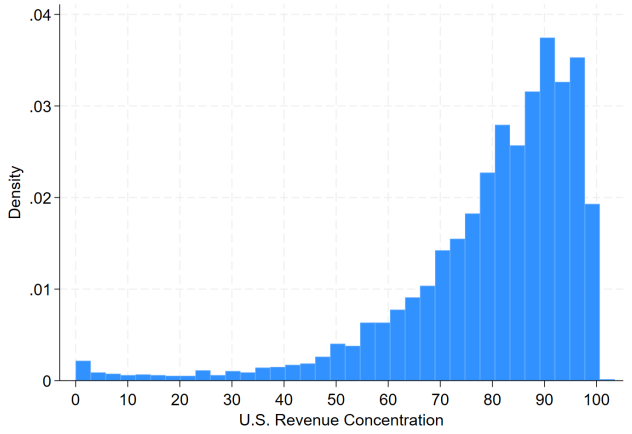


Figure 3: Unadjusted long-short returns of portfolios sorted on TAV

This figure presents the long-short portfolios based on firm exposure to abnormal temperature variability (TAV). States are sorted each month into quartiles or quintiles based on TAV. Firms are then assigned to portfolios according to the geographic concentration measure, and value-weighted average returns are computed for each group. The plotted lines represent the monthly return difference between the lowest and highest TAV exposure portfolios: the yellow line corresponds to the quartile sort, and the blue dashed line to the quintile sort.

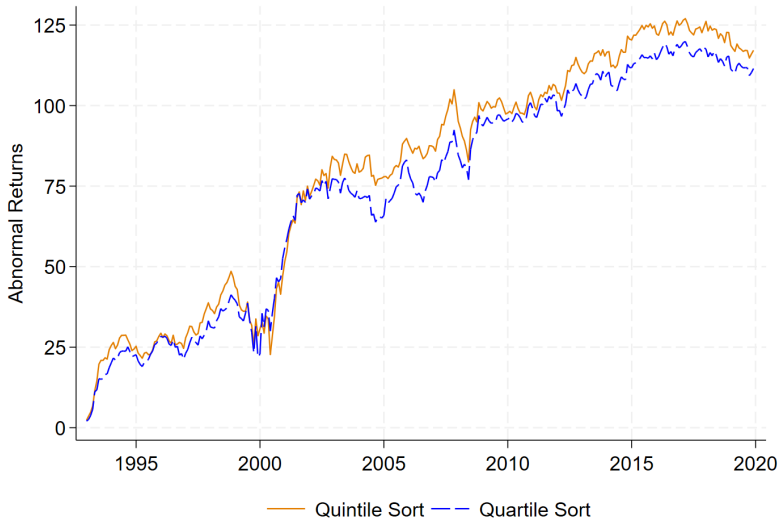
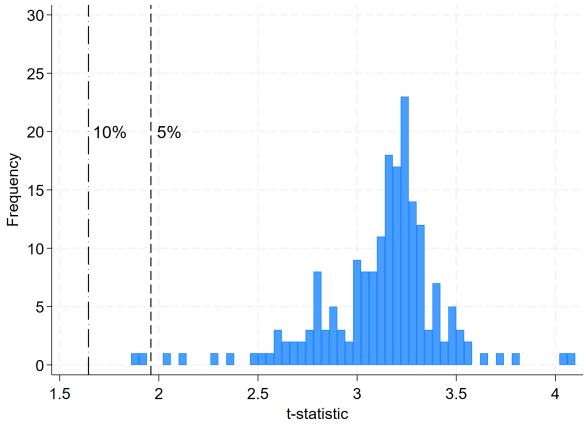


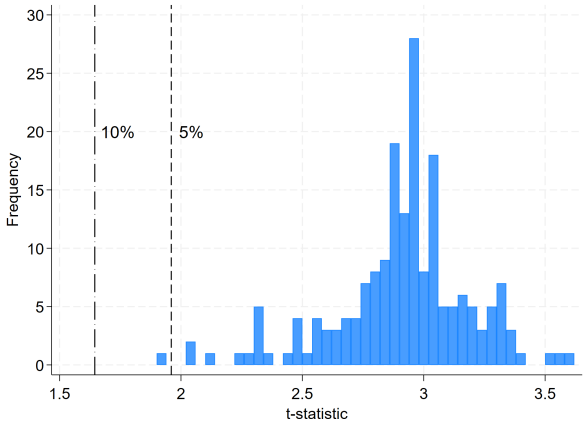
Figure 4: Abnormal returns t-statistics

This figure presents histograms of t-statistics from regressions of long-short portfolio returns (based on quartile (panel (a)) and quintile (panel (b)) sorts) on the Fama-French 3-factor model, each augmented with one of the 189 anomaly predictors from Chen and Zimmermann (2022). Vertical dashed lines indicate 10% and 5% significance thresholds, adjusted for multiple hypothesis testing using the Benjamini-Hochberg procedure for the False Discovery Rate.

(a) Quartile Sorts



(b) Quintile Sorts



8 Tables

Table 1: Summary Statistics

This table presents summary statistics of each variable. The panels describe the data frequency and specify whether the variable is measured at the US state or national level. Firm- or household-level variables such as returns or expenditures are winsorized at 1%. Table A.1 in the Appendix presents variable definitions.

Variable	Mean	STDV	P10	P25	Median	P75	P90	N
Panel (A): State Monthly Variables								
TAV	-0.032	(0.716)	-0.847	-0.478	-0.080	0.362	0.851	15,552
TA	0.293	(2.005)	-2.158	-0.939	0.273	1.562	2.778	15,552
Precipitation	0.060	(1.310)	-1.378	-0.691	-0.071	0.653	1.609	15,552
Wildfire	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
Wildfire	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
Wildfire	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	0.000	0.190	0.390	0.562	324
CAPE	26.710	(6.181)	20.381	22.280	25.872	29.299	35.835	324
Term Spread	1.148	(0.887)	0.070	0.290	1.170	1.890	2.380	324
Value Spread	1.652	(0.171)	1.417	1.564	1.645	1.751	1.883	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
Wildfire, 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 with which US states transition between different quartile or quintile sorts of abnormal temperature anomaly TAV. Panel A presents the transition matrix based on quartile sorting, while Panel B presents the matrix for quintile sorts. The sample period is 1993–2019. The leftmost column of each panel indicates the initial exposure quartile (Panel A) or quintile (Panel B) for a given month. The remaining columns represent the exposure tier the state moves to in the following month. Each cell shows the percentage of times a state moves from one percentile to another.

Panel A: Quartile sorts

	Quartiles			
	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 sorts

	Quintiles				
	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: Spearman Rank Correlations of Abnormal Temperature Variability

This table reports the persistence of exposure rankings over a six-month horizon. To show that cross-sectional exposure to temperature variability is geographically and temporally transient, i.e., rotating across states from month to month, we compute state-level TAV each month and rank states into quartiles or quintiles based on their contemporaneous realized exposure. We then calculate the Spearman rank correlation coefficients (ρ) between the rankings in month t and month $t + k$, where the lag k ranges from 1 to 6. The sharp decline in correlation coefficients after the first month indicates that the shocks captured by our measure are short-lived and do not persist as a stable state characteristic.

Lag Months (k)	Quartile Sort (ρ)	Quintile Sort (ρ)
1	0.194	0.201
2	0.020	0.023
3	0.021	0.028
4	0.040	0.039
5	0.023	0.022
6	0.016	0.010

Table 4: Abnormal returns to portfolios sorted on TAV

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to abnormal temperature variability (TAV). Each month t, we sort US states into four or five groups based on their realized TAV. Firms headquartered in these states are assigned to the corresponding portfolios, and their returns are value-weighted and rebalanced monthly. Portfolio 1 includes firms operating in states experiencing the lowest values of TAV (low variability). Portfolios 4 or 5 include firms in states experiencing the highest values of TAV (high variability). Middle portfolios are grouped together by equal-weighting their returns and denoted as either "Portfolios 2,3" or "Portfolios 2,3,4". We report abnormal returns for each portfolio after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. The final row, "Portfolio 1–5" or "Portfolio 1–4", reports the return spread between the least and most exposed portfolios. The sample includes 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 generate more than 73% of their revenues in the US. 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 5: Iterative Variance Decomposition Results

This table reports the variance decomposition of unexpected returns for long–short portfolios sorted on abnormal temperature variability (TAV). Panel A uses a quartile sort: the portfolio goes long firms in states in the lowest TAV quartile and short firms in states in the highest TAV quartile. Panel B uses a quintile sort: the portfolio goes long firms in states in the lowest TAV quintile and short firms in states in the highest TAV quintile. We decompose the variance of unexpected returns into cash-flow news (Var(CF)), discount-rate news (Var(DR)), and their covariance (Cov(CF,DR)) using the vector autoregression framework of Campbell (1991). Columns report an iterative expansion of the VAR state vector: (1) lagged portfolio return; (2) adds the market excess return (Mkt_RF); (3) adds the value spread (VS), defined as the difference in log book-to-market ratios between small-value and small-growth stocks; (4) adds the cyclically adjusted price-to-earnings ratio (CAPE); (5) adds the term spread (TERM), defined as the yield difference between 10-year and 2-year Treasury bonds; and (6) adds innovations in the WSJ Climate Change News Index (Engle et al., 2020). The rows report Var(CF), Var(DR), Cov(CF,DR), the number of observations, and the predictive R^2 from the return equation. The sample runs from January 1993 to December 2019, except for specifications including WSJ innovations, which end in June 2017 due to data availability. The discount factor ρ is set to 0.97.

	(1)	(2)	(3)	(4)	(5)	(6)
	Autocorr	**+Mkt**	**+VS**	**+CAPE**	**+TERM**	**+WSJ**
Panel A: Quartile L/S portfolio returns						
Var(CF)	4.733	4.731	5.225	5.021	5.288	6.063
Var(DR)	0.034	0.036	0.400	0.361	0.483	0.922
Cov(CF,DR)	-0.402	-0.401	0.041	-0.079	0.129	0.616
Obs	323	323	323	323	323	293
R-sq	0.008	0.008	0.013	0.014	0.018	0.030
Panel B: Quintile L/S portfolio returns						
Var(CF)	5.884	5.882	6.663	6.447	6.729	7.739
Var(DR)	0.002	0.003	0.788	0.685	0.905	1.546
Cov(CF,DR)	-0.102	-0.101	0.707	0.548	0.814	1.529
Obs	323	323	323	323	323	293
R-sq	0.000	0.001	0.009	0.009	0.014	0.027

Table 6: Temperature exposure and revenues

This table presents the results of regressing quarterly revenue, scaled by total assets from the prior quarter, on 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 US 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 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 US 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: Household expenditure sensitivity to temperature

This table presents regressions relating abnormal temperature variability (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 **??**. 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	-0.007***	-0.007**	-0.023*	0.013**	0.004	-0.008	-0.018**	-0.007***	-0.008**	-0.022*	0.012**	0.004	-0.008	-0.018**
	(-3.095)	(-2.458)	(-1.908)	(2.204)	(0.668)	(-1.110)	(-2.154)	(-3.284)	(-2.622)	(-1.819)	(2.067)	(0.696)	(-1.193)	(-2.184)
TA								-0.001	-0.001	0.003	-0.006***	0.001	-0.002	-0.001
								(-1.320)	(-1.180)	(0.747)	(-3.288)	(0.473)	(-1.265)	(-0.216)
Precipitation								-0.000	-0.000	-0.007	-0.002	0.002	-0.003	0.001
								(-0.354)	(-0.357)	(-1.016)	(-0.705)	(0.528)	(-0.991)	(0.330)
Wildfire								0.000	-0.000	-0.001	-0.001	-0.001	-0.001	0.000
								(1.138)	(-0.315)	(-0.866)	(-0.509)	(-0.753)	(-1.553)	(0.707)
CPI, yoy	0.012**	0.001	0.001	0.053***	0.006	-0.005	-0.001	0.012**	0.001	0.002	0.053***	0.007	-0.004	-0.001
	(2.216)	(0.229)	(0.045)	(7.659)	(0.745)	(-0.496)	(-0.046)	(2.178)	(0.238)	(0.067)	(7.611)	(0.830)	(-0.429)	(-0.066)
HPI, yoy	0.001	-0.051	0.634*	0.074	-0.049	0.209*	0.258	-0.001	-0.053	0.637*	0.065	-0.047	0.204	0.257
	(0.020)	(-0.747)	(1.947)	(0.757)	(-0.353)	(1.703)	(1.473)	(-0.014)	(-0.767)	(1.963)	(0.615)	(-0.329)	(1.662)	(1.473)
Income, yoy	-0.020	0.046	-0.310	-0.115	-0.022	0.200*	-0.078	-0.019	0.047	-0.315	-0.107	-0.019	0.206	-0.079
	(-0.449)	(1.051)	(-1.277)	(-1.248)	(-0.131)	(1.690)	(-0.546)	(-0.441)	(1.081)	(-1.289)	(-1.218)	(-0.118)	(1.678)	(-0.546)
Unrate, yoy	0.002	-0.017	-0.047	0.012	0.039	0.046**	-0.003	0.003	-0.015	-0.050	0.018	0.042	0.050**	-0.003
	(0.224)	(-1.511)	(-1.062)	(0.584)	(1.465)	(2.058)	(-0.094)	(0.252)	(-1.388)	(-1.121)	(0.942)	(1.540)	(2.194)	(-0.107)
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	0.582	0.469	0.079	0.388	0.242	0.244	0.184	0.582	0.469	0.079	0.388	0.242	0.244	0.184
Observations	405917	405368	246428	381581	331937	367856	327362	405917	405368	246428	381581	331937	367856	327362

Table 9: Minutes worked on the prior day

This table reports OLS regressions of minutes worked on the day prior to the interview on abnormal temperature variability (TAV) computed over the preceding 15 days. The dependent variable is the respondent's minutes worked yesterday from the American Time Use Survey. The first two rows report coefficients on TAV and its interaction with HighRisk, an indicator equal to one for respondents employed in "high-risk" industries—agriculture, forestry, fishing and hunting, mining, construction, manufacturing, transportation, and utilities, following Graff Zivin and Neidell (2014), and zero otherwise (wholesale and retail trade, information, professional and business services, educational and health services, leisure and hospitality, other services, and public administration). Control variables include age, marital/cohabitation status, education, race, household income, employment status, sex, and day-of-week fixed effects. We include industry-by-year and state-by-quarter fixed effects. TA, Precipitation, and Wildfire are state-level physical-risk variables computed over the same 15-day window. Standard errors are clustered at the state level; standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) 2003-2019	(2) 2003-2019	(3) 2003-2019	(4) 2007-2014
HighRisk × TAV	-2.688**	-2.693**	-2.700**	-3.878**
	(1.335)	(1.336)	(1.337)	(1.599)
TAV	-0.347	-0.359	-0.450	0.163
	(0.546)	(0.561)	(0.561)	(1.058)
HPI, yoy		-5.747	-5.469	25.790
		(13.805)	(13.812)	(17.886)
Income, yoy		5.349**	5.537**	-0.670
		(2.375)	(2.433)	(2.545)
Unrate, yoy		1.187	1.610	-2.007
		(5.795)	(5.748)	(7.689)
TA			-0.554**	-0.122
			(0.223)	(0.349)
Precipitation			-0.390	0.307
			(0.433)	(0.519)
Burning			-0.062	0.069
			(0.135)	(0.186)
Controls	Yes	Yes	Yes	Yes
IndxYear	Yes	Yes	Yes	Yes
StatexQ	Yes	Yes	Yes	Yes
Adj R Squared	0.345	0.345	0.345	0.337
Observations	130058	130058	130058	60709

Table 10: TAV and state-specific climate attention

This table presents regression results of the quarterly Google Search index for "Climate Change" on temperature anomaly (TA) and abnormal temperature variability (TAV) with varying fixed effects. Standard errors are clustered by US state, and t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, 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)
Wildfire			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 11: TAV and the Wall Street Journal News Index

This table presents regression results of the quarterly Engle et al. (2020) Wall Street Journal news index on abnormal temperature variability (TAV). The dependent variable is multiplied by 1,000, and specifications include varying fixed effects. T-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, 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)
Wildfire					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 12: The impact TAV on the attention paid by earnings call participants to climate risk

This table presents the association between the physical climate exposure attention index developed by Sautner et al. (2023) and yearly abnormal temperature variability (TAV). The yearly innovations in the attention index is regressed onto TAV with industry fixed effects. We control for national attention towards climate change. WSJ Innov represents the innovations in the national Wall Street Journal news index developed by Engle et al. (2020). 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 year. We also include deviations in average temperature, precipitation, and wildfire risk. 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 ***, **, *.

	(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)
Wildfire			-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 13: Fama Macbeth Volatility Regressions

This table reports Fama-MacBeth regressions from monthly cross-sectional regressions of the log of idiosyncratic return volatility on 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, from the prior quarter. 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)
TAV	0.162***	0.174***	0.241***	0.127***	0.175***	0.109***	0.054**
	(4.046)	(4.300)	(5.200)	(4.251)	(5.281)	(3.536)	(2.076)
TA					0.035		
					(0.339)		
Precipitation					-0.147***		
					(-3.411)		
Wildfire					0.038		
					(0.222)		
Analyst Dispersion							0.028***
							(2.642)
WSJ						0.001***	
						(3.346)	
IVOL, lag 1				-0.345***	-0.286***	-0.269***	-0.583***
				(-9.188)	(-6.932)	(-5.897)	(-22.775)
VIX, changes			-0.230***	-0.175***	-0.193***	-0.192***	-0.103***
			(-9.529)	(-9.674)	(-9.355)	(-11.179)	(-8.566)
Return, lag 1		0.187***	0.163***	0.110***	0.126***	0.117***	0.122***
		(16.280)	(15.009)	(10.404)	(14.018)	(11.464)	(12.461)
Leverage	0.000	0.000	0.000	0.000	-0.000	0.000**	0.000
	(0.808)	(0.874)	(0.158)	(0.451)	(-0.456)	(2.004)	(0.569)
Total Assets	-0.002	-0.002	-0.001	-0.001	0.007***	0.009***	0.004*
	(-1.219)	(-1.381)	(-0.911)	(-0.630)	(2.711)	(2.668)	(1.824)
Bk to Mkt	0.004**	0.006***	0.006***	0.004***	0.009**	0.006*	0.002
	(2.514)	(2.954)	(3.080)	(2.722)	(2.491)	(1.699)	(1.364)
Tobins Q	-0.001***	-0.001***	-0.001***	-0.001***	0.001	0.003**	0.001
	(-3.931)	(-3.736)	(-3.545)	(-2.726)	(0.791)	(2.317)	(1.417)
PPE/Assets	0.001	0.000	0.000	0.001	0.003	-0.001	-0.003**
	(0.547)	(0.258)	(0.376)	(0.991)	(1.480)	(-0.688)	(-2.090)
ROA	-0.065	-0.071	-0.096	-0.122**	-0.081	0.038	0.099*
	(-1.151)	(-1.218)	(-1.532)	(-2.269)	(-1.231)	(0.553)	(1.936)
Unrate, yoy	-0.000	-0.001	-0.001	0.001	0.000	0.001	0.002
	(-0.061)	(-0.274)	(-0.479)	(0.521)	(0.072)	(0.103)	(0.978)
HPI, yoy	-0.000	0.000	-0.000	-0.000	-0.001	-0.000	0.000
	(-0.145)	(0.174)	(-0.058)	(-0.243)	(-0.713)	(-0.260)	(1.425)
Income, yoy	-0.003***	-0.003***	-0.002***	-0.002***	-0.003**	-0.003*	-0.002***
	(-4.007)	(-3.865)	(-3.545)	(-3.000)	(-2.051)	(-1.936)	(-3.598)
Industry FE	No	No	No	No	Yes	Yes	Yes
ADJ R Squared	0.010	0.030	0.039	0.050	0.070	0.072	0.116
Observations	873288	859124	857684	847933	821298	768188	429168

Table 14: Temperature exposure and analyst earnings surprises

This table presents the results of regressing quarterly earnings-per-share surprises on abnormal temperature variability (TAV). Earnings-per-share surprises are multiplied by 100 for clarity. The 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 either firm or 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) Mean	(6) Mean	(7) Mean	(8) Mean
TAV	0.045**	0.045**	0.021**	0.005	-0.074**	-0.075***	-0.076***	-0.045***
	(2.484)	(2.420)	(2.311)	(0.804)	(-2.494)	(-2.865)	(-3.788)	(-2.881)
L.Total Assets	0.087***	0.063***	0.143***	0.071**	0.152***	0.247***	0.189***	0.724***
	(10.480)	(7.003)	(11.740)	(2.339)	(6.937)	(8.212)	(4.574)	(3.933)
L.Bk to Mkt	0.201***	0.219***	0.140***	0.081***	-0.147**	-0.227***	-0.847***	-1.206***
	(10.139)	(10.917)	(7.804)	(5.004)	(-2.579)	(-3.746)	(-7.999)	(-4.219)
L.ROA	-0.005***	-0.004***	-0.002***	-0.001***	0.038***	0.036***	0.021***	0.004***
	(-13.741)	(-12.937)	(-12.594)	(-7.289)	(37.380)	(36.315)	(23.126)	(5.090)
L.Tobins Q	0.028***	0.023**	0.017*	0.006	-0.168***	-0.152***	-0.168***	-0.155***
	(3.318)	(2.231)	(1.855)	(0.891)	(-3.120)	(-2.822)	(-3.449)	(-3.627)
L.PPE/Assets	0.084***	0.076***	0.070***	0.035	-0.110***	-0.070***	-0.248***	-0.371***
	(5.155)	(5.578)	(4.996)	(1.639)	(-8.342)	(-5.003)	(-4.650)	(-5.310)
L.Leverage	0.515***	0.565***	0.447***	0.372***	0.579***	0.291***	-0.854***	-0.147
	(8.108)	(9.253)	(8.304)	(4.430)	(4.926)	(2.731)	(-2.961)	(-0.275)
HPI, yoy	-1.561***	-1.535***	-1.262***	-0.241*	-0.245	-0.370	-0.321	-0.095
	(-8.605)	(-8.851)	(-8.030)	(-1.819)	(-0.492)	(-0.844)	(-0.885)	(-0.104)
Income, yoy	0.024	0.042	0.054*	0.107	0.596*	0.493*	0.549**	1.821***
	(0.204)	(0.398)	(1.774)	(0.983)	(1.777)	(1.821)	(2.138)	(4.470)
Unrate, yoy	-0.216***	-0.225***	-0.039	0.158***	-0.831***	-0.773***	-0.460***	-0.277**
	(-4.189)	(-4.283)	(-1.301)	(6.167)	(-6.777)	(-6.590)	(-5.650)	(-2.432)
Analysts, Number		0.011***	0.016***	0.015***		-0.040***	-0.008*	-0.002
		(3.213)	(11.783)	(9.073)		(-7.944)	(-1.762)	(-0.487)
TA				-0.003				0.015**
				(-1.213)				(2.322)
Precipitation				0.002				0.002
				(0.429)				(0.174)
Wildfire				0.000				0.002
				(0.102)				(1.126)
Firm FE	No	No	Yes	No	No	No	Yes	No
FirmxYear FE	No	No	No	Yes	No	No	No	Yes
Adj R Squared	0.117	0.119	0.457	0.625	0.179	0.187	0.321	0.555
Obs	158925	155280	154935	149094	198924	185039	184757	178493

Table 15: Yale Climate Change Survey

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)
Wildfire		-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

A Appendix

A.1 Placebo tests

To assess whether our results could be driven by spurious correlations, we implement two placebo tests that preserve the structure of the temperature data. First, we randomly shuffle TAV values across states within each month (cross-sectional permutations). Second, we shuffle TAV values within each state over time (time series permutations). Using these randomized allocations, we repeat our long-short portfolio procedure: sorting into quartile or quintile portfolios and estimating monthly abnormal returns by regressing the long-short returns on the Fama-French 3 factor model.

We repeat this procedure 5,000 times and plot the distribution of estimated abnormal returns in Figure A.1. Panels (a) and (b) show results for quartile sorts, and panels (c) and (d) for quintile sorts. The distributions are approximately normal, with dashed vertical lines indicating the abnormal returns from our actual specification (0.362 for quartile sorts and 0.373 for quintile sorts). In both cases, fewer than 0.4% of placebo estimates exceed these values, suggesting the observed return patterns are unlikely to arise by chance or from state-level structure alone. Moreover, the normally distributed alphas indicate that our original state-level sorting procedure does not inherently favor states with more firms.

A.2 Lagged effects of temperature variability

To test for a delayed market response to abnormal temperature variability, we replicate our long-short portfolio strategy using TAV lagged by one and two months.[22]

Panel A of Table A.2 shows that a long-short portfolio sorted on one-month lagged TAV earns statistically significant abnormal returns of 26 basis points per month (3.16% annualized). In contrast, Panel B of Table A.2 shows that the abnormal returns for portfolios sorted on two-month lagged TAV are statistically indistinguishable from zero. This lagged relationship suggests that markets do not fully incorporate the impact of temperature shocks in the month they occur. In unreported results, quartile sorts present the same relationship.

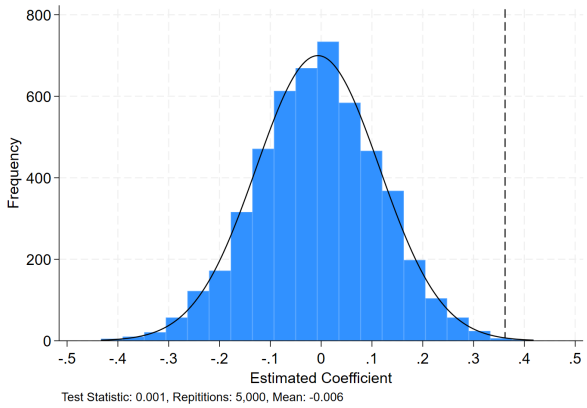
[22]Our main results show a contemporaneous negative response of returns to TAV. However, there may be a delay in how the market incorporates such information, as evidenced by Cuculiza et al. (2025).

A.3 Figures

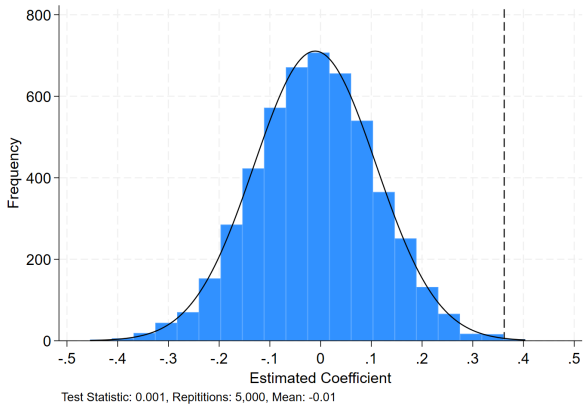
Figure A.1: Placebo tests: alpha coefficients after controlling for FF3 factors

This figure presents the Fama-French 3-factor adjusted alphas from a long-short strategy that sorts the 48 US 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.

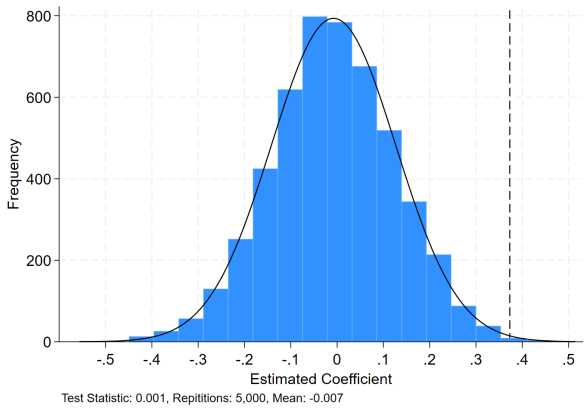
(a) Quartile sort: cross-sectional shuffle



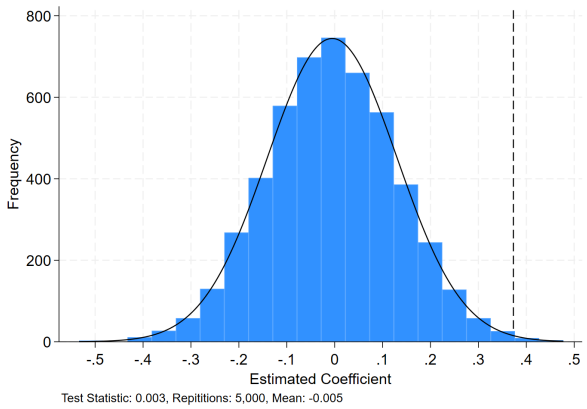
(b) Quartile sort: time-series shuffle



(c) Quintile sort: cross-sectional shuffle



(d) Quintile sort: time-series shuffle



A.4 Tables

Table A.1: Definition of variables used.

Panel A: Weather and Climate Variables (Source: NOAA, gridMET)	
Variable	Definition
TAV	A measure of the standard deviation of temperature anomalies for a given month, quarter, or year in a US state, minus the previous 25-year historical standard deviation for the same period and state. Source: nClimGrid (NOAA).
TA	The monthly, quarterly, or yearly average temperature anomaly in a US state minus the previous 25-year historical average for the same period and state. Source: nClimGrid (NOAA).
Precipitation	This variable captures state-level precipitation deviations from a 13-year rolling historical average, calculated using gridMET data.
Wildfire	The gridMET wildfire index, which proxies for fire containment effort. It is defined as the state-level deviation from a 13-year rolling historical baseline.
Panel B: Firm Level Variables (Sources: Compustat, I/B/E/S, CRSP.	
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	Plant, property, and equipment divided by total assets. ln(PPENTQ/ATQ).
Forecast Dispersion, ln	The natural log of the standard deviation of analyst estimates. Source: I/B/E/S.
Mean Surprise/L1.Price, %	Average difference between reported earnings and the mean analyst estimate 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 Sections 1A, 2, 6, and 7 of annual 10-K filings to count US state mentions. The ratio is the number of mentions of the firm's headquarter state divided by the total mentions of all US states (Garcia & 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.
Panel C: State Variables (Sources: Yale Climate Opinion, Federal Reserve Bank Of St. Louis, Google)	
Yale Exposure, Innov	The percentage of respondents in each state who report personally experiencing the effects of global warming.
Yale Happening, Innov	Survey data on the percentage of respondents in the US who believe climate change is happening in a US state.
Yale Harm, Innov	Survey data on the percentage of respondents in a US state who think global warming will harm people in the US.
Population	Yearly population (POP) for each US state.
HPI, yoy	The year-over-year growth rate of the All-Transactions House Price Index (STHPI).
Income, yoy	The year-over-year growth rate of the Total Personal Income (OTOT).
Unrate, yoy	The year-over-year growth rate of the Unemployment Rate for each US state.
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.

Variable definitions continued.

Panel D: Time Series Data	
Variable	Definition
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.
Value Spread	Difference in the log book-to-market ratios between small-value and small-growth stocks. Source: Ken French's data store.
CAPE	Cyclically adjusted price-to-earnings ratio. Source: Robert Shiller's data store.
Term Spread	Difference between 10- and 2-year Treasury bonds. Source: Federal Reserve Bank Of St. Louis.
Panel E: 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 on 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	Family income before tax (fincbtax). Continuous.
Age	Age of respondent (age_ref). Continuous.
Rooms	Number of rooms (roomsq). Continuous.
Family Size	Family size (fam_size). Continuous.
Earners	Number of earners in the family (no_earnr). Continuous.
Sex	Sex of respondent (sex_ref). Categorical.
Urban	Household is urban (bls_urbn). Categorical.
Marital Status	Marital status of respondent (martial1). Categorical.
Education	Education of respondent (educ_ref). Categorical.
Race	Race of respondent (ref_race). Categorical.
Housing Tenure	How long they have been in the house for (cutenure). Categorical.
Panel F: 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 A.2: Abnormal returns to portfolios sorted on one and two month lagged TAV

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to abnormal temperature variability (TAV), lagged by one (Panel A) and two (Panel B) months. Each month (either $t-1$ or $t-2$) we sort US states into five groups based on their realized TAV. Firms headquartered in these states are assigned to the corresponding portfolios, and their returns are value-weighted and rebalanced monthly at time t. Portfolio 1 includes firms operating in states experiencing the lowest values of TAV (low variability). Portfolio 5 includes firms in states experiencing the highest values of TAV (high variability). Middle portfolios are grouped together by equal-weighting their returns and denoted as "Portfolios 2,3,4". We report abnormal returns for each portfolio after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. The final row, "Portfolio 1–5", reports the return spread between the least and most exposed portfolios. The sample includes 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 generate more than 73% of their revenues in the US. 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: One month lagged quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.190**	0.144	0.147	0.099	0.113
	(0.086)	(0.097)	(0.095)	(0.114)	(0.102)
Portfolios 2, 3, 4	0.068	0.018	0.007	-0.079	-0.068
	(0.097)	(0.055)	(0.055)	(0.060)	(0.053)
Portfolio 5	-0.075	-0.113	-0.096	-0.164*	-0.155
	(0.109)	(0.102)	(0.099)	(0.092)	(0.095)
Portfolio 1 - 5	0.265**	0.257*	0.244*	0.263*	0.269*
	(0.129)	(0.134)	(0.137)	(0.156)	(0.146)

Panel B: Two month lagged quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.163**	0.118	0.120	0.044	0.090
	(0.073)	(0.092)	(0.093)	(0.125)	(0.100)
Portfolios 2, 3, 4	0.038	-0.009	-0.022	-0.125**	-0.115**
	(0.093)	(0.063)	(0.061)	(0.061)	(0.058)
Portfolio 5	-0.030	-0.049	-0.029	-0.017	-0.042
	(0.094)	(0.092)	(0.087)	(0.092)	(0.100)
Portfolio 1 - 5	0.194	0.167	0.148	0.061	0.132
	(0.133)	(0.133)	(0.137)	(0.152)	(0.129)

B Internet Appendix

B.1 Temperature variability

This section contrasts our abnormal temperature variability measure (TAV) against commonly used temperature and weather metrics. We contrast TAV with rolling average temperature anomalies (TA) and with standard measures of extremes and intensity, showing that variability captures tail dynamics that the mean misses. We also document that TAV is distinct from precipitation and wildfire indicators, supporting its interpretation as a separate dimension of physical climate risk.

B.1.1 Dynamics

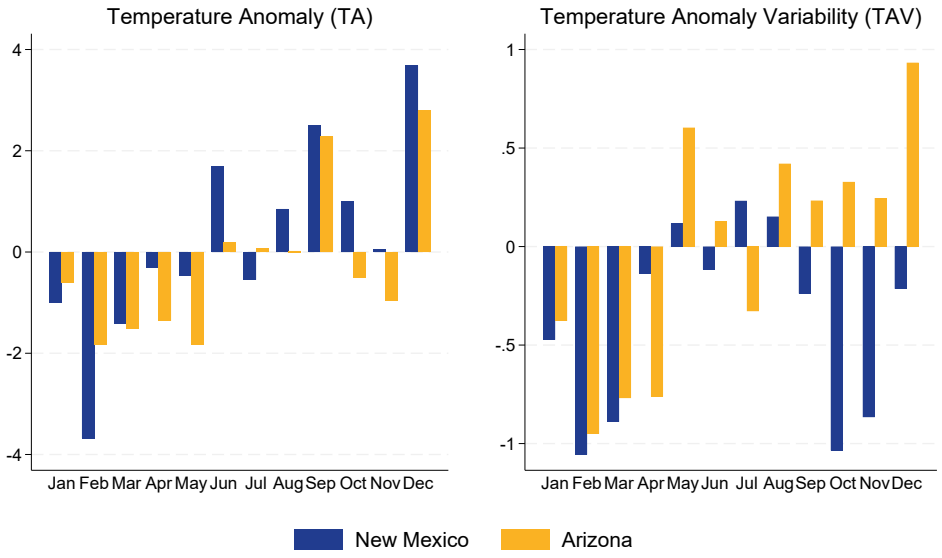
While prior research generally shows the frequency of temperature extremes is more sensitive to variability than to the mean (Katz and Brown, 1992), we compare our construction of TAV to alternative temperature metrics and weather variables in this section. Our main comparison is with the rolling average temperature anomaly, TA, which is widely used in the financial and economic literature (Choi et al., 2020; Cuculiza et al., 2025). We also evaluate TAV alongside measures such as the number of days above a given temperature threshold, temperature intensity, precipitation, and wildfire metrics.

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). We begin with a simple illustrative comparison between TA and TAV using data from New Mexico and Arizona in 2010, before turning to more formal statistical analyses of their differences. The left panel in Figure B.1 shows the TA for New Mexico (blue) and Arizona (yellow). The right panel shows TAV for the same states. Despite both states experiencing comparable average temperature anomalies in 2010 (except in a few instances), 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 highlights that states experiencing the similar average temperature anomaly may nevertheless face more adverse temperature effects due to higher abnormal temperature variability. Details of the

methodology for spatially aggregating each measure to the state and country levels at various frequencies, such as quarterly or yearly—which are consistent with financial data reporting periods—are provided in Section B.1.2 of this Internet Appendix.

Figure B.1: TA and TAV in New Mexico and Arizona

The left panel shows the temperature anomaly (TA) for New Mexico (in blue) and Arizona (in yellow). The right panel shows the abnormal temperature variability—here titled Temperature Anomaly Variability (TAV), for the same states. The year of reference is 2010. 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 2010, Arizona exhibits greater variability in temperature anomalies.



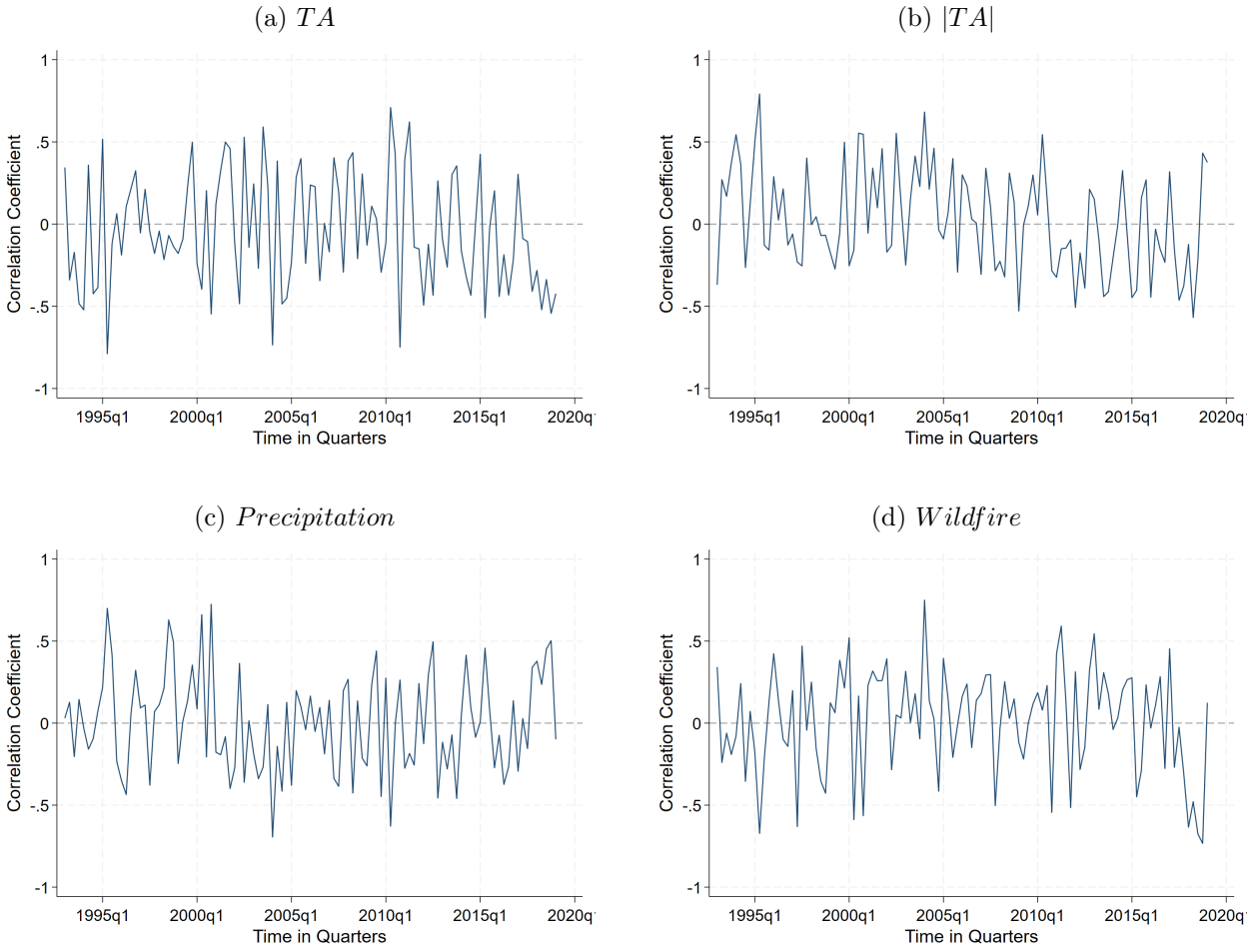
Next, we compute the average correlation between TAV and three commonly used metrics of climate-induced physical risk across all US states by quarter from 1993 to 2019: TA and the absolute value of TA, average deviations in mean precipitation, and average deviations in wildfire risk. Across all panels, the results reveal that TAV is largely uncorrelated with these alternative measures, suggesting that abnormal temperature volatility captures distinct dimensions of climate-induced physical risk.[23]

The emerging financial literature has increasingly explored the link between financial

[23]Using the absolute value of TA incorporates both colder-than-normal and hotter-than-normal temperatures as as deviations from the baseline, enabling a symmetric assessment of how temperature anomalies, regardless of direction, affect outcomes.

Figure B.2: Quarterly correlation between TAV and other weather variables

This figure presents the monthly correlation between TAV and $|TA|$, TA, precipitation, and the wildfire index across all states from 1993 to 2019.



outcomes and temperature extremes, typically defined as the number of unusually cold and hot days. Building on this, we now examine the ability of TAV to capture *periods* of extreme and intense temperatures.

To quantify temperature extremes by specific dates (day d, month m, year y) and locations, we return to the temperature anomaly distribution from 1993 to 2019 for each state s, following the methodology outlined in Section 2. Then, using matching percentile pairs from the historical 25-year rolling temperature anomaly distribution, we define extreme temperature days using various percentile thresholds, such as below the 30th percentile for cold days and above the 70th for hot days, extending to the 2.5th and 97.5th percentiles. 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 fall outside these thresholds.

These tests allow us to benchmark TAV against existing measures used in the financial literature. For example, Pankratz et al. (2023) and Addoum et al. (2020) categorize extremes using a 30°C or 32°C threshold, associating worker performance declines beyond this point. Addoum et al. (2023) extends this by examining the effects of the entire temperature distribution on firms' earnings news—notably including colder extremes. To address adaptation concerns, Acharya et al. (2022) and Pankratz et al. (2023) compare realized temperatures against historical distributions.

We use the calculated number of days 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 B.3 shows the standardized coefficients of TA (orange) and TAV (blue)—coefficients multiplied by the metrics' respective standard deviations—across five 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 percentile ranges indicate that it better captures the incidence of both cold and hot extreme temperature days. A one-standard-deviation increase in TAV is associated with over two additional extreme temperature days per quarter. In contrast, TA displays a markedly weaker link with the frequency of such extremes.

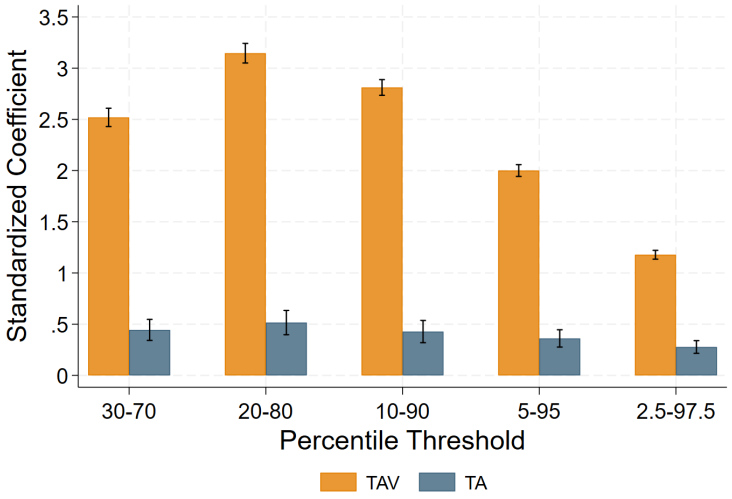
Next, rather than counting the frequency of extreme days, we examine how TAV and TA relate to the intensity or severity of extreme temperatures on days that exceed threshold values. Measuring severity matters because larger anomaly magnitudes plausibly generate greater effects.[24]

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. We focus on the right tail of the temperature anomaly distribution, since most of the existing literature emphasizes heat extremes. To examine how temperature metrics relate to the intensity

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

Figure B.3: Capturing dynamics at both tails of the distribution

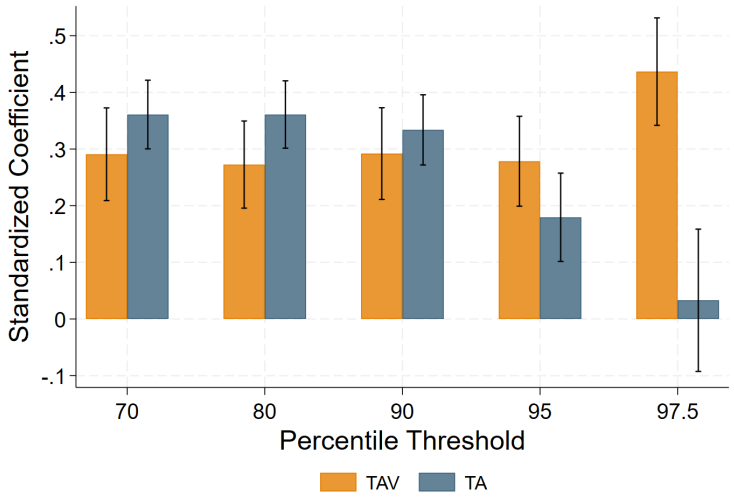
This figure displays the standardized coefficients of TAV (orange) and TA (blue), derived from regression analysis where the number of extreme days in a quarter and state is regressed on either TAV or TA. The coefficients are then "standardized" by multiplying each by its respective metrics' standard 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 $z_{s,[q,y]} = \alpha + \beta_1 \text{TA}_{s,[q,y]} + \epsilon_{s,q,y}$ and $z_{s,[q,y]} = \alpha + \beta_1 \text{TAV}_{s,[q,y]} + \epsilon_{s,q,y}$, where z is the number of extreme temperature days based on the percentile pairs for each unique combination of quarter, year, and state (q, y, s). The coefficients highlight that TAV better captures the incidence of extreme temperatures than TA does.



of extreme temperatures, we regress the state-level quarterly mean temperature anomaly, conditional on exceeding each of the five percentile thresholds, on either TAV or TA. Figure B.4 shows the standardized coefficients that indicate how strongly each metric is linked to the intensity of extreme temperatures. We find that TAV better captures intense temperature extremes in comparison to TA. 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.

Figure B.4: Intensity of extreme hot temperatures

This figure displays the standardized coefficients of TAV (orange) and TA (blue), derived from a regression analysis where the mean temperature anomaly, conditional on days exceeding a specified percentile threshold in a quarter, is regressed on either TA or TAV. The coefficients are then standardized by multiplying each by their respective metrics' standard deviation. We define extremes by calculating the rolling 25-year percentiles 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 quarter for the days exceeding the threshold—a measure of temperature intensity. This graph reports the coefficients on TA and TAV of the regression $z_{s,[q,y]} = \alpha + \beta_1 \text{TA}_{s,[q,y]} + \epsilon_{s,q,y}$ and $z_{s,[q,y]} = \alpha + \beta_1 \text{TAV}_{s,[q,y]} + \epsilon_{s,q,y}$, where z is the average temperature anomaly for each unique combination of quarter, year, and state (q, y, s). The coefficients suggest TAV provides a stronger representation of extreme heat conditions compared to TA.

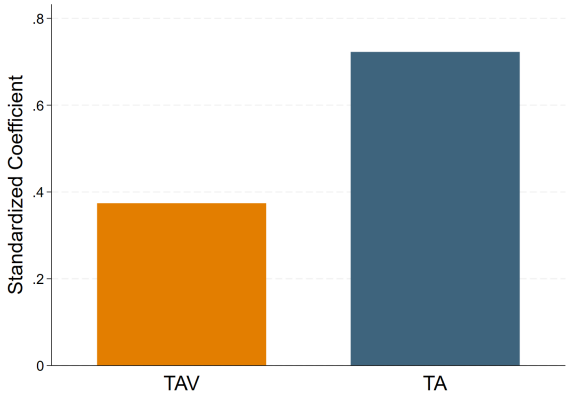


As an additional test, we follow Pankratz et al. (2023) and Addoum et al. (2020) to categorize extremes as temperatures above a 30°C threshold. For each quarter we calculate the number of days exceeding these thresholds for each state between 1993 and 2019. We

then regress the number of days that exceed the threshold on TA and TAV with quarter fixed effects. Figure B.5 presents the standardized coefficients of TAV (orange) and TA (blue) from regressions explaining the number of days above this threshold. The results show that TAV has an effect size roughly half that of TA in capturing days above this threshold. One possible explanation is that heatwaves often span several consecutive days, which can raise the average temperature anomaly more than the variability measure.

Figure B.5: 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 quarter 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 $y_{s,[q,y]} = \alpha + \beta_1 \text{TA}_{s,[q,y]} + \beta_2 \text{TAV}_{s,[q,y]} + \omega_q + \epsilon_{s,q,y}$, 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.



B.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 NOAA's nClimGrid-Daily data, roughly 0.0417 degrees latitude and longitude, we calculate a state-aggregated temperature index as follows:

$$T_{s,[d,m,y]} = \sum_{i=1}^{N_s} w_i \cdot T_{i,[d,m,y]}, \tag{12}$$

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 $1/N_s$.[25] Thus, $T_{s,[d,m,y]}$ is an equally weighted average of the temperature assigned to each grid cell in state s. This spatial aggregation enables us to derive TA and TAV for each state s in the US, as outlined in Expressions (1) and (4).

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 is population-based weights. Population-based weights prioritize human experiences; thus, greater variability in a more populated state holds more significance than in a sparsely populated one. We therefore construct the country-level TAV measure as follows:

$$TAV_{US,[m,y]} = \sum_{s=1}^{N_{states}} \left(\frac{\text{Pop}_{s,y}}{\text{Pop}_{US,y}} \right) \cdot TAV_{s,[m,y]}, \tag{13}$$

where $TAV_{US,[m,y]}$ is the country-level temperature measure for month m and year y. $TAV_{s,[m,y]}$ is the corresponding state-level measure. The weight is the ratio of the state's yearly population to the total US yearly population, which we obtain via the "POP" code from the Federal Reserve Bank of St. Louis. The same procedure is performed for our other weather variables: TA, precipitation, and wildfire risk.

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

B.2 Other robustness

This section evaluates whether our return and performance results are sensitive to alternative empirical designs and dependence assumptions. We first verify the cross-sectional pricing of TAV using Fama–MacBeth regressions with a set of firm- and state-level controls and complementary double-sorts that address size-related concerns. We then assess the sensitivity of TAV to the choice of historical window used to form climate normals and adjust inference for spatial dependence using Conley (1999) standard errors. Finally, we show that the return patterns are specific to temperature variability, and do not arise from alternative physical risk measures such as mean temperature anomalies, precipitation, or wildfire exposure.

B.2.1 Fama-Macbeth regressions and double sorts

We use Fama-MacBeth regressions to estimate the cross-sectional return association with abnormal temperature variability, incorporating a comprehensive set of firm- and state-level controls. Firm-level controls include the log of total assets, log book-to-market equity, and the log of plant, property, and equipment over assets, as well as leverage, return on assets, and Tobin's Q. State-level controls include year-over-year changes in the unemployment rate, house price index, and personal income. Column (1) of Table B.1 presents baseline results using these controls, showing a negative contemporaneous relationship between TAV and returns, consistent with our portfolio-level findings. Columns (2) through (6) provide additional robustness by sequentially introducing other risk factors and industry fixed effects. These include 12 Fama-French industry sectors, plus construction and transportation, which are particularly sensitive to weather conditions (Graff Zivin and Neidell, 2014). In Column (4) we include innovations in the Wall Street Journal Climate Change News Index from Engle et al. (2020) to account for unexpected market-wide shifts in climate-related investor attention.[26] Column (6) includes additional state-level physical climate risk factors, such as average temperature (TA), average precipitation, and a wildfire index. Across all specifications, firms earn lower returns when abnormal TAV materializes, reinforcing our interpretation that these returns reflect the contemporaneous pricing of idiosyncratic spatio-temporal temperature shocks.

[26] We examine the role of attention in greater detail in Section 5.2.

We also address concerns related to firm size by performing a double sort on abnormal temperature variability and firm total assets. First, we categorize states into terciles based on TAV, and further sort firms within each tercile into two groups using their total assets from the previous quarter as a proxy for size. Panels A and B in Table B.2 confirm that the return pattern persists across both small and large firms, with larger contemporaneous effects observed among smaller firms, which tend to be more geographically concentrated.

Table B.1: Fama Macbeth Return Regressions

This table reports Fama-MacBeth regression coefficients from monthly cross-sectional regressions of individual stock abnormal returns on exposure to abnormal temperature variability (TAV). All regressions include 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 a quarter ago. 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 control for state-level deviations in average temperature, precipitation, and wildfire risk. Firms are included if their headquartered state is mentioned at least 5% of the time in their 10-K filings (the 10th percentile) relative to mentions of all other states, and if more than 73% of their revenues are generated within the US. The sample period spans January 1993 to December 2019. Statistical significance is denoted by * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. T-statistics are in parentheses and are calculated using the Newey-West correction for 12 lags.

	(1)	(2)	(3)	(4)	(5)	(6)
TAV	-0.030***	-0.025**	-0.035***	-0.037***	-0.028**	-0.032**
	(-2.591)	(-2.258)	(-2.836)	(-2.809)	(-2.079)	(-2.385)
TA						-0.063*
						(-1.694)
Precipitation						0.048***
						(3.006)
Wildfire						-0.114
						(-1.563)
WSJ				0.000***		
				(2.742)		
Ret, Lag 1					0.010***	0.009***
					(4.193)	(3.592)
Leverage	-0.000*	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.959)	(-1.373)	(-0.334)	(-0.848)	(-1.037)	(-0.440)
Total Assets	0.002***	0.002***	0.005***	0.004**	0.004***	0.004***
	(3.550)	(4.221)	(3.344)	(2.470)	(3.218)	(3.240)
Bk to Mkt	0.001	0.001	0.001	0.003*	0.001	0.001
	(0.954)	(1.008)	(1.249)	(1.735)	(1.116)	(1.353)
Tobins Q	0.000	0.000	0.000	-0.000	0.000	0.000
	(0.747)	(1.023)	(1.235)	(-0.193)	(1.175)	(0.573)
PPE/Assets	-0.000	-0.001	-0.001	-0.001	-0.001	-0.001
	(-0.440)	(-1.123)	(-1.421)	(-0.582)	(-0.924)	(-1.169)
ROA	0.024	0.027	0.017	-0.000	0.024	0.038
	(1.160)	(1.146)	(0.459)	(-0.017)	(0.928)	(1.336)
Unrate, yoy	0.000	0.000	0.002	0.002	0.002	0.002
	(0.390)	(0.494)	(0.528)	(0.652)	(0.593)	(0.558)
HPI, yoy	0.000	0.000	-0.000	-0.000	-0.000	-0.000
	(0.079)	(0.839)	(-0.865)	(-1.099)	(-1.300)	(-1.174)
Income, yoy	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(-1.344)	(-1.369)	(-0.806)	(-0.389)	(-0.728)	(-0.500)
Mkt	0.196	0.251	0.288	0.302	0.255	0.257
	(0.832)	(1.127)	(1.219)	(1.174)	(1.079)	(1.098)
SMB		0.036	-0.017	0.011	-0.051	-0.066
		(0.297)	(-0.127)	(0.078)	(-0.380)	(-0.489)
HML		-0.002	0.013	0.049	-0.024	-0.030
		(-0.013)	(0.086)	(0.306)	(-0.154)	(-0.191)
Industry FE	No	No	Yes	Yes	Yes	Yes
ADJ R Squared	0.041	0.075	0.081	0.091	0.081	0.086
Observations	873287	871311	851217	790690	835215	828372

Table B.2: Abnormal returns to portfolios sorted on TAV and size, 3x2

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to abnormal temperature variability (TAV) and size. Each month t, we sort US states into three groups (terciles) based on their realized TAV. Firms are then assigned to these TAV terciles according to the location of their headquarters. Within each tercile, we split firms into two groups based on total assets measured at the end of the prior quarter. Portfolio returns are calculated as the value-weighted abnormal returns of firms headquartered in each group, with monthly rebalancing. Panel A presents results for smaller firms, and Panel B for larger firms. Portfolio 1 contains firms operating in states with the lowest TAV values (low variability), while Portfolio 3 contains firms in states with the highest TAV (high variability). We report portfolio abnormal returns after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. Return spreads such as "Portfolio 1–3" report the return spread between firms in the lowest and highest TAV terciles, conditional on firm size. To ensure geographic relevance, we include only 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 generate more than 73% of their revenues within in the US 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	0.277	0.336**	0.354**	0.390**	0.450***
	(0.189)	(0.141)	(0.143)	(0.153)	(0.125)
Portfolios 2	-0.176	-0.119	-0.099	-0.140	-0.075
	(0.171)	(0.102)	(0.101)	(0.120)	(0.129)
Portfolio 3	-0.199	-0.152	-0.144	-0.191	-0.040
	(0.168)	(0.117)	(0.118)	(0.125)	(0.128)
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	0.238**	0.189***	0.196***	0.162**	0.154**
	(0.102)	(0.073)	(0.072)	(0.080)	(0.068)
Portfolios 2	0.019	-0.031	-0.044	-0.177**	-0.167*
	(0.097)	(0.084)	(0.081)	(0.084)	(0.096)
Portfolio 3	-0.123**	-0.150**	-0.155***	-0.179***	-0.162**
	(0.063)	(0.060)	(0.057)	(0.061)	(0.069)
Portfolio 1-3	0.361***	0.339***	0.351***	0.341***	0.317***
	(0.117)	(0.104)	(0.102)	(0.113)	(0.111)

B.2.2 Other rolling windows

The empirical tests use a rolling window of 25 years to calculate abnormal temperatures. This window was chosen to select a middle-ground between climate science which suggests calculating normals over a 30 year window and behavioral evidence where agents are able to remember climates across long periods of time. Here, we conduct our main empirical tests using 20 and 30 year windows to show that selecting 25 years does not arbitrarily change our results.

Tables B.3 and B.4 present the results of portfolios sorted using either a 20 or 30-year historical window to calculate TAV. Overall, the results confirm that the relationship between TAV and firm performance is not contingent on the historical window used.

Table B.3: Abnormal returns to portfolios sorted on TAV, 20-year window

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to differences in the standard deviation of temperature anomalies, abnormal temperature variability (TAV). A 20-year historical rolling window is used to calculate climate normals. Each month t, we sort US 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 US. 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	0.189**	0.153**	0.165**	0.137	0.139**
	(0.087)	(0.075)	(0.076)	(0.087)	(0.070)
Portfolios 2, 3	0.060	0.011	-0.002	-0.101	-0.102
	(0.095)	(0.058)	(0.057)	(0.048)	(0.061)
Portfolio 4	-0.100	-0.118	-0.113	-0.132	-0.113
	(0.067)	(0.071)	(0.067)	(0.073)	(0.081)
Portfolio 1 - 4	0.289**	0.271**	0.278***	0.268**	0.252**
	(0.114)	(0.109)	(0.105)	(0.115)	(0.117)

Panel B: Quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.180*	0.147	0.157*	0.132	0.120
	(0.099)	(0.092)	(0.092)	(0.095)	(0.085)
Portfolios 2, 3, 4	0.078	0.027	0.012	-0.080	-0.078
	(0.101)	(0.055)	(0.053)	(0.043)	(0.048)
Portfolio 5	-0.141	-0.157	-0.152	-0.204	-0.189
	(0.085)	(0.086)	(0.081)	(0.080)	(0.087)
Portfolio 1 - 5	0.322**	0.305**	0.309**	0.336***	0.309**
	(0.136)	(0.127)	(0.123)	(0.124)	(0.122)

Table B.4: Abnormal returns to portfolios sorted on TAV, 30-year window

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to differences in the standard deviation of temperature anomalies, abnormal temperature variability (TAV). A 30-year historical rolling window is used to calculate climate normals. Each month t, we sort US 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 US. 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	0.235**	0.198**	0.203**	0.186**	0.173**
	(0.103)	(0.083)	(0.083)	(0.092)	(0.077)
Portfolios 2, 3	0.038	-0.009	-0.018	-0.120*	-0.116
	(0.093)	(0.071)	(0.071)	(0.072)	(0.078)
Portfolio 4	-0.167**	-0.179**	-0.170**	-0.182**	-0.161*
	(0.080)	(0.081)	(0.072)	(0.074)	(0.082)
Portfolio 1 - 4	0.402***	0.377***	0.373***	0.368***	0.334***
	(0.135)	(0.113)	(0.107)	(0.110)	(0.113)

Panel B: Quintile portfolios

	Market	FF3-Factor	FF3+Liq	FF3+Liq+BAB	FF5+Mom+Liq
Portfolio 1	0.182*	0.143*	0.150*	0.133	0.124
	(0.101)	(0.085)	(0.086)	(0.093)	(0.080)
Portfolios 2, 3, 4	0.070	0.021	0.007	-0.091*	-0.076
	(0.104)	(0.062)	(0.061)	(0.046)	(0.059)
Portfolio 5	-0.202**	-0.211**	-0.200***	-0.210***	-0.206**
	(0.084)	(0.084)	(0.077)	(0.079)	(0.084)
Portfolio 1-5	0.384***	0.354***	0.351***	0.344***	0.330**
	(0.145)	(0.125)	(0.118)	(0.125)	(0.134)

B.2.3 Spatial autocorrelation

The empirical analysis thus far has allowed for arbitrary correlation among observations within states through clustering. This approach accounts for any measurement error or shocks shared by observations within the same state. However, if correlations extend across state lines, then state-level clustering will understate the standard errors. Temperature, much like the operations of firms, often covers wider regions and spills across state lines. In such cases, clustering at the state level will underestimate the standard errors.

To account for spatial autocorrelation, we use Conley (1999) standard errors that correct for spatial dependence based on proximity. Specifically, the standard errors allow for non-zero correlation and heterogeneity across space and also account for serial correlation within units over time. Since temperature shocks may exhibit strong spatial dependence, the adjustment could produce more reliable inference.

The correction requires a distance bandwidth. Hansen et al. (1981) finds that temperatures at stations 500 km and 1,000 km apart in the midlatitudes have correlations of about 0.8 and 0.5, respectively. In the contiguous US, the average distance between state centroids and their neighbors is about 471 km.[27] With these considerations, we use 500 km and 1,000 km as cutoff thresholds, assuming zero correlation for pairs beyond these distances. These ranges capture both neighboring and more distant spatial dependence.

Tables B.5 and B.6 show the results from applying specification 5 from Section 4.3 to firm asset-scaled revenues and profitability, using a 500 km threshold. Standard errors allow for first-order autocorrelation (a one-quarter lag). Tables B.7 and B.8 show a similar estimation but with a longer 1,000 km threshold.

Overall, the results largely match those produced in Section 4.3 with an average negative effect of TAV on asset-scaled revenues and profitability. There remains 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. Similarly, a significant positive relationship exists for these ratios and TAV for the Energy industry.

The relationship between revenues and TAV is no longer significant for utilities, di-

[27] This is calculated using the Haversine formula.

verging from our main results. Utilities operate networks of power grids, gas lines, or water systems that may span multiple states where temperature and economic shocks may spill over state borders. Therefore, utilities located near each other tend to move together as they are affected by similar weather patterns, regulatory environments, or market shocks. This spatial correlation suggests neighboring utilities do not provide independent information for inference.

Table B.5: Temperature exposure and revenues, 500 km spatial dependence

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 US. All dependent and independent variables, except for TAV, are winsorized at 1%. All specifications include firm-by-year fixed effects. Standard errors are calculated using the Conley (1999) HAC estimator with a 500 km spatial cutoff and a heteroskedasticity and autocorrelation consistent correction allowing for serial correlation up to one quarterly lag. 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	-0.17**	-0.28***	0.03	-0.31	0.16	0.44*	-0.09	-0.28**	-0.13***	-0.56***	-0.11	-0.41*	-0.14	-0.02	0.30
	(-2.38)	(-2.84)	(0.14)	(-1.12)	(0.74)	(1.85)	(-0.92)	(-2.51)	(-3.12)	(-2.62)	(-0.55)	(-1.73)	(-0.89)	(-0.11)	(1.39)
L.Total Assets	-13.81***	-13.47***	-14.42***	-11.64***	-18.84***	-5.42***	-14.10***	-15.99***	-8.78***	-15.34***	-15.18***	-22.40***	-11.01***	-17.22***	-5.67***
	(-39.91)	(-31.70)	(-10.09)	(-7.37)	(-10.76)	(-3.66)	(-17.24)	(-17.99)	(-8.89)	(-10.89)	(-18.15)	(-16.43)	(-5.94)	(-11.62)	(-3.48)
L.Bk to Mkt	-1.95***	-2.01***	-2.88***	-2.56***	-3.28***	-1.75***	-1.47***	-2.65***	0.16	-3.05***	-1.16***	-3.43***	-0.63***	-1.23***	-4.27***
	(-18.86)	(-12.36)	(-4.80)	(-4.94)	(-4.96)	(-3.91)	(-6.03)	(-10.34)	(1.27)	(-5.51)	(-4.75)	(-6.86)	(-2.91)	(-2.87)	(-3.82)
L.ROA	-0.01***	0.00	-0.01	-0.00	-0.00	0.01**	0.00**	0.00	-0.00	-0.02***	0.00	-0.05***	0.01	0.00	-0.01
	(-6.41)	(0.16)	(-1.41)	(-0.11)	(-0.39)	(2.27)	(2.20)	(0.98)	(-1.41)	(-3.71)	(0.37)	(-11.34)	(1.41)	(0.02)	(-1.63)
L.Tobins Q	-0.05	-0.28***	0.20	0.80	-0.85	1.09***	-0.11	0.01	2.08***	0.78*	0.27*	-0.67	-0.02	0.58	1.18
	(-0.93)	(-4.83)	(0.42)	(1.63)	(-1.25)	(2.96)	(-1.02)	(0.07)	(5.70)	(1.86)	(1.94)	(-1.28)	(-0.09)	(1.45)	(0.48)
L.PPE/Assets	0.96***	2.49***	0.17	2.07***	1.88	-0.55	0.73**	-0.73	0.79**	-0.59	1.23***	-0.62	1.10	3.96***	-11.68***
	(6.04)	(10.00)	(0.23)	(2.65)	(1.61)	(-0.39)	(2.29)	(-1.21)	(2.46)	(-0.67)	(2.62)	(-0.72)	(1.33)	(4.10)	(-4.76)
L.Leverage	1.24*	-3.12**	6.66**	-0.24	0.01	-4.59**	-1.26	4.49***	1.76*	21.56***	-0.59	4.03	0.71	-8.79***	47.00***
	(1.85)	(-2.31)	(2.11)	(-0.10)	(0.00)	(-2.23)	(-0.87)	(3.03)	(1.74)	(8.15)	(-0.34)	(1.57)	(0.32)	(-3.12)	(7.05)
Unrate, yoy	-1.63***	-1.80***	-2.43**	-1.40	-3.72***	-2.74*	-0.74	-2.56***	-0.28	-2.17**	-1.75**	-2.58***	0.03	-4.11***	-1.57*
	(-5.69)	(-3.86)	(-1.98)	(-1.22)	(-2.86)	(-1.87)	(-1.28)	(-4.73)	(-1.54)	(-2.07)	(-2.52)	(-3.20)	(0.05)	(-5.66)	(-1.91)
HPI, yoy	1.60	1.30	-12.05**	9.84	-10.88	9.23	1.21	2.86	1.63	-3.81	1.97	5.18	7.99	3.06	0.90
	(0.76)	(0.45)	(-2.23)	(1.50)	(-1.50)	(0.89)	(0.48)	(0.59)	(1.37)	(-0.59)	(0.45)	(1.12)	(1.49)	(0.64)	(0.16)
Income, yoy	5.58***	10.86***	15.68*	7.96*	15.36*	36.41***	0.00	9.44***	0.33	2.04	5.66**	7.01**	3.06	7.91**	4.00
	(3.79)	(4.28)	(1.91)	(1.65)	(1.68)	(3.35)	(0.00)	(3.51)	(0.57)	(0.82)	(1.98)	(1.99)	(0.91)	(2.09)	(1.20)
FirmYear FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centered R Sq		0.14	0.10	0.05	0.09	0.04	0.14	0.11	0.13	0.05	0.08	0.06	0.20	0.12	0.10
Observations		48380	4668	10434	7198	8754	27524	22292	67490	15913	24812	33134	6314	9826	10853

Table B.6: Temperature exposure and profitability, 500 km spatial dependence

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 US. All dependent and independent variables, except for TAV, are winsorized at 1%. All specifications include firm-by-year fixed effects. Standard errors are calculated using the Conley (1999) HAC estimator with a 500 km spatial cutoff and a heteroskedasticity and autocorrelation consistent correction allowing for serial correlation up to one quarterly lag. 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***	-0.03	-0.09**	-0.03***	-0.19***	0.01	-0.08*	-0.08	-0.09*	0.02
	(-3.00)	(-2.53)	(-1.28)	(-2.44)	(-0.18)	(2.61)	(-0.55)	(-2.47)	(-2.81)	(-4.15)	(0.24)	(-1.91)	(-0.96)	(-1.66)	(0.44)
L.Total Assets	-0.08	-0.19	0.14	-0.25	-0.16	-1.91***	1.82***	-0.62**	-0.34***	-1.06***	-0.57***	-0.13	0.20	-0.44	-0.63***
	(-0.86)	(-0.88)	(0.24)	(-1.17)	(-0.42)	(-4.56)	(7.28)	(-2.28)	(-3.39)	(-3.75)	(-2.81)	(-0.63)	(0.58)	(-1.39)	(-2.86)
L.Bk to Mkt	-1.22***	-1.40***	-1.92***	-1.31***	-1.56***	-1.87***	-1.02***	-1.71***	-0.37***	-1.28***	-1.39***	-1.48***	-0.78***	-1.15***	-1.40***
	(-25.67)	(-11.10)	(-5.65)	(-7.23)	(-6.23)	(-6.08)	(-7.50)	(-11.96)	(-7.82)	(-8.11)	(-9.71)	(-13.38)	(-3.71)	(-6.62)	(-4.69)
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
	(-10.60)	(-6.51)	(-3.88)	(-5.40)	(-2.33)	(0.35)	(-3.67)	(-5.61)	(-2.80)	(-6.50)	(-8.23)	(-13.61)	(-1.54)	(-4.27)	(-1.63)
L.Tobins Q	-0.13***	-0.13***	-0.38	-0.01	-0.43***	0.19	-0.20***	-0.29***	0.17*	-0.08	-0.16**	-0.33***	-0.16	-0.35***	-0.29
	(-5.14)	(-2.99)	(-1.64)	(-0.07)	(-2.76)	(0.98)	(-3.99)	(-3.41)	(1.86)	(-0.74)	(-2.24)	(-5.07)	(-1.29)	(-2.60)	(-0.47)
L.PPE/Assets	-0.66***	-1.14***	0.42	-0.42	0.59*	-0.89**	-0.60***	-0.69***	0.02	-0.35*	-0.56***	-1.10***	-0.66**	-0.59	-1.46***
	(-10.28)	(-8.02)	(0.83)	(-1.56)	(1.75)	(-2.02)	(-3.23)	(-3.28)	(0.31)	(-1.78)	(-4.28)	(-6.78)	(-2.07)	(-1.12)	(-3.63)
L.Leverage	0.17	0.46	-0.54	1.11*	0.22	0.15	-2.84***	0.68	0.17	5.18***	0.10	0.90**	-4.25***	-1.75**	10.62***
	(1.00)	(0.99)	(-0.52)	(1.73)	(0.25)	(0.13)	(-5.39)	(1.24)	(0.63)	(7.69)	(0.22)	(2.26)	(-4.00)	(-2.09)	(9.86)
Unrate, yoy	-0.95***	-1.37***	-1.44**	-0.97***	-2.26***	-2.32***	-0.74***	-1.47***	-0.21***	-1.61***	-1.00***	-0.64***	-2.36***	-0.59**	-0.32*
	(-6.87)	(-4.11)	(-2.49)	(-3.04)	(-4.72)	(-2.76)	(-3.27)	(-5.73)	(-2.95)	(-5.63)	(-3.82)	(-2.83)	(-3.64)	(-2.25)	(-1.72)
HPI, yoy	-0.73	-1.84**	-2.49	2.99**	-1.84	-2.47	-2.68**	-2.03	1.41***	-0.27	-0.50	0.68	-0.94	0.97	-0.97
	(-1.50)	(-1.99)	(-1.02)	(2.18)	(-1.03)	(-0.59)	(-2.31)	(-1.43)	(4.63)	(-0.24)	(-0.44)	(0.58)	(-0.51)	(0.75)	(-0.82)
Income, yoy	1.03**	-0.36	3.50	2.59**	1.88	10.97**	-0.21	2.01**	0.44*	0.11	1.53	0.09	4.99**	1.28	0.86
	(2.40)	(-0.29)	(1.17)	(2.21)	(0.70)	(1.98)	(-0.15)	(2.11)	(1.90)	(0.14)	(1.46)	(0.11)	(1.98)	(1.44)	(1.05)
FirmYear FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centered R Sq		0.02	0.05	0.04	0.04	0.08	0.02	0.04	0.01	0.04	0.03	0.05	0.03	0.03	0.09
Observations		47248	4624	10368	7123	8629	26798	22148	67300	15681	24525	32734	6211	9770	10842

Table B.7: Temperature exposure and revenues, 1000 km spatial dependence

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 US. All dependent and independent variables, except for TAV, are winsorized at 1%. All specifications include firm-by-year fixed effects. Standard errors are calculated using the Conley (1999) HAC estimator with a 1000 km spatial cutoff and a heteroskedasticity and autocorrelation consistent correction allowing for serial correlation up to one quarterly lag. 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	-0.17**	-0.28**	0.03	-0.31	0.16	0.44*	-0.09	-0.28**	-0.13***	-0.56**	-0.11	-0.41	-0.14	-0.02	0.30
	(-2.00)	(-2.55)	(0.13)	(-0.94)	(0.69)	(1.83)	(-0.90)	(-2.05)	(-2.66)	(-2.41)	(-0.50)	(-1.55)	(-0.84)	(-0.09)	(1.18)
L.Total Assets	-13.81***	-13.47***	-14.42***	-11.64***	-18.84***	-5.42***	-14.10***	-15.99***	-8.78***	-15.34***	-15.18***	-22.40***	-11.01***	-17.22***	-5.67***
	(-37.07)	(-30.43)	(-10.21)	(-6.92)	(-10.97)	(-3.66)	(-16.90)	(-16.39)	(-8.81)	(-10.75)	(-17.49)	(-17.29)	(-5.94)	(-11.84)	(-3.28)
L.Bk to Mkt	-1.95***	-2.01***	-2.88***	-2.56***	-3.28***	-1.75***	-1.47***	-2.65***	0.16	-3.05***	-1.16***	-3.43***	-0.63***	-1.23***	-4.27***
	(-16.22)	(-11.87)	(-4.87)	(-4.77)	(-4.77)	(-3.92)	(-5.99)	(-9.33)	(1.19)	(-5.38)	(-4.80)	(-6.57)	(-2.80)	(-2.90)	(-3.70)
L.ROA	-0.01***	0.00	-0.01	-0.00	-0.00	0.01**	0.00**	0.00	-0.00	-0.02***	0.00	-0.05***	0.01	0.00	-0.01
	(-5.78)	(0.16)	(-1.36)	(-0.10)	(-0.39)	(2.25)	(2.15)	(0.96)	(-1.43)	(-3.40)	(0.37)	(-10.52)	(1.44)	(0.02)	(-1.36)
L.Tobins Q	-0.05	-0.28***	0.20	0.80*	-0.85	1.09***	-0.11	0.01	2.08***	0.78*	0.27*	-0.67	-0.02	0.58	1.18
	(-0.86)	(-4.80)	(0.43)	(1.66)	(-1.25)	(2.96)	(-0.97)	(0.07)	(5.64)	(1.85)	(1.87)	(-1.31)	(-0.09)	(1.52)	(0.47)
L.PPE/Assets	0.96***	2.49***	0.17	2.07**	1.88	-0.55	0.73**	-0.73	0.79**	-0.59	1.23***	-0.62	1.10	3.96***	-11.68***
	(5.46)	(9.20)	(0.22)	(2.57)	(1.63)	(-0.38)	(2.28)	(-1.17)	(2.44)	(-0.66)	(2.67)	(-0.67)	(1.32)	(4.16)	(-4.63)
L.Leverage	1.24*	-3.12**	6.66**	-0.24	0.01	-4.59**	-1.26	4.49***	1.76*	21.56***	-0.59	4.03	0.71	-8.79***	47.00***
	(1.67)	(-2.36)	(2.02)	(-0.11)	(0.00)	(-2.22)	(-0.89)	(2.81)	(1.83)	(8.50)	(-0.33)	(1.47)	(0.32)	(-3.26)	(6.46)
Unrate, yoy	-1.63***	-1.80***	-2.43*	-1.40	-3.72***	-2.74*	-0.74	-2.56***	-0.28	-2.17*	-1.75**	-2.58***	0.03	-4.11***	-1.57
	(-4.93)	(-3.68)	(-1.87)	(-0.97)	(-2.67)	(-1.88)	(-1.20)	(-4.08)	(-1.23)	(-1.79)	(-2.16)	(-3.04)	(0.04)	(-4.59)	(-1.45)
HPI, yoy	1.60	1.30	-12.05**	9.84	-10.88	9.23	1.21	2.86	1.63	-3.81	1.97	5.18	7.99	3.06	0.90
	(0.69)	(0.43)	(-2.17)	(1.29)	(-1.48)	(0.89)	(0.45)	(0.54)	(1.24)	(-0.55)	(0.42)	(1.10)	(1.38)	(0.51)	(0.14)
Income, yoy	5.58***	10.86***	15.68*	7.96	15.36*	36.41***	0.00	9.44***	0.33	2.04	5.66**	7.01**	3.06	7.91**	4.00
	(3.60)	(4.03)	(1.74)	(1.63)	(1.73)	(3.29)	(0.00)	(3.41)	(0.58)	(0.77)	(2.05)	(1.97)	(0.83)	(2.14)	(1.22)
FirmYear FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centered R Sq		0.14	0.10	0.05	0.09	0.04	0.14	0.11	0.13	0.05	0.08	0.06	0.20	0.12	0.10
Observations		48380	4668	10434	7198	8754	27524	22292	67490	15913	24812	33134	6314	9826	10853

Table B.8: Temperature exposure and profitability, 1000 km spatial dependence

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 US. All dependent and independent variables, except for TAV, are winsorized at 1%. All specifications include firm-by-year fixed effects. Standard errors are calculated using the Conley (1999) HAC estimator with a 1000 km spatial cutoff and a heteroskedasticity and autocorrelation consistent correction allowing for serial correlation up to one quarterly lag. 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**	-0.03	-0.09**	-0.03***	-0.19***	0.01	-0.08*	-0.08	-0.09	0.02
	(-2.53)	(-2.47)	(-1.21)	(-2.16)	(-0.17)	(2.45)	(-0.51)	(-2.05)	(-2.58)	(-4.19)	(0.23)	(-1.73)	(-0.89)	(-1.42)	(0.39)
L.Total Assets	-0.08	-0.19	0.14	-0.25	-0.16	-1.91***	1.82***	-0.62**	-0.34***	-1.06***	-0.57***	-0.13	0.20	-0.44	-0.63***
	(-0.80)	(-0.85)	(0.24)	(-1.13)	(-0.43)	(-4.27)	(6.88)	(-2.23)	(-3.34)	(-3.70)	(-2.74)	(-0.62)	(0.58)	(-1.35)	(-2.67)
L.Bk to Mkt	-1.22***	-1.40***	-1.92***	-1.31***	-1.56***	-1.87***	-1.02***	-1.71***	-0.37***	-1.28***	-1.39***	-1.48***	-0.78***	-1.15***	-1.40***
	(-22.39)	(-11.43)	(-5.57)	(-7.12)	(-5.89)	(-5.80)	(-7.33)	(-10.89)	(-7.75)	(-8.45)	(-10.15)	(-12.92)	(-3.75)	(-6.33)	(-4.56)
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
	(-8.75)	(-5.91)	(-3.80)	(-5.48)	(-2.20)	(0.34)	(-3.38)	(-5.18)	(-2.74)	(-5.99)	(-7.51)	(-13.26)	(-1.52)	(-4.13)	(-1.57)
L.Tobins Q	-0.13***	-0.13***	-0.38	-0.01	-0.43***	0.19	-0.20***	-0.29***	0.17*	-0.08	-0.16**	-0.33***	-0.16	-0.35***	-0.29
	(-4.88)	(-3.11)	(-1.63)	(-0.09)	(-2.72)	(0.97)	(-4.00)	(-3.28)	(1.86)	(-0.77)	(-2.52)	(-4.91)	(-1.46)	(-2.64)	(-0.46)
L.PPE/Assets	-0.66***	-1.14***	0.42	-0.42	0.59*	-0.89**	-0.60***	-0.69***	0.02	-0.35*	-0.56***	-1.10***	-0.66**	-0.59	-1.46***
	(-9.76)	(-7.61)	(0.85)	(-1.47)	(1.74)	(-1.99)	(-3.23)	(-3.23)	(0.31)	(-1.66)	(-4.26)	(-6.64)	(-2.06)	(-1.11)	(-3.48)
L.Leverage	0.17	0.46	-0.54	1.11*	0.22	0.15	-2.84***	0.68	0.17	5.18***	0.10	0.90**	-4.25***	-1.75**	10.62***
	(1.01)	(1.02)	(-0.52)	(1.74)	(0.25)	(0.13)	(-5.48)	(1.20)	(0.65)	(7.76)	(0.21)	(2.36)	(-4.18)	(-2.07)	(8.88)
Unrate, yoy	-0.95***	-1.37***	-1.44**	-0.97**	-2.26***	-2.32**	-0.74***	-1.47***	-0.21**	-1.61***	-1.00***	-0.64**	-2.36***	-0.59**	-0.32
	(-5.10)	(-3.88)	(-2.23)	(-2.56)	(-3.86)	(-2.52)	(-2.88)	(-4.07)	(-2.48)	(-4.92)	(-3.71)	(-2.39)	(-3.21)	(-2.09)	(-1.49)
HPI, yoy	-0.73	-1.84*	-2.49	2.99**	-1.84	-2.47	-2.68**	-2.03	1.41***	-0.27	-0.50	0.68	-0.94	0.97	-0.97
	(-1.37)	(-1.90)	(-1.03)	(2.05)	(-0.90)	(-0.57)	(-2.22)	(-1.35)	(4.72)	(-0.24)	(-0.44)	(0.56)	(-0.48)	(0.70)	(-0.75)
Income, yoy	1.03**	-0.36	3.50	2.59**	1.88	10.97*	-0.21	2.01*	0.44*	0.11	1.53	0.09	4.99*	1.28	0.86
	(2.12)	(-0.28)	(1.09)	(2.12)	(0.66)	(1.81)	(-0.15)	(1.88)	(1.76)	(0.14)	(1.39)	(0.10)	(1.85)	(1.40)	(1.14)
FirmYear FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Centered R Sq		0.02	0.05	0.04	0.04	0.08	0.02	0.04	0.01	0.04	0.03	0.05	0.03	0.03	0.09
Observations		47248	4624	10368	7123	8629	26798	22148	67300	15681	24525	32734	6211	9770	10842

B.2.4 Other physical risks and portfolio sorts

As an additional robustness check for our portfolio sorting exercise, we repeat the analysis using alternative weather-related phenomena as the primary sorting criteria. This extension is motivated by the broader impacts of climate change, which include not only temperature variability but also anomalies in precipitation and wildfire risk (Allan and Soden, 2008). Specifically, we examine whether average deviations in temperature anomalies (TA), precipitation, and the wildfire index can explain cross-sectional variation in returns. The portfolio construction procedure follows the long-short methodology outlined previously.

Table B.9 reports the results of quartile and quintile sorts using TA, calculated as in Equation 2. We find no evidence of contemporaneous return difference between firms located in warmer (portfolio 1) and colder (portfolios 4 or 5) regions. The lack of significant effects for TA is consistent with prior findings by Addoum et al. (2020) and Addoum et al. (2023), who similarly report no immediate market response to extreme temperature levels.

To account for deviations in both directions—hotter and colder than usual—we also compute the absolute value of monthly temperature anomalies, $|TA|$. We modify equation 1 accordingly to calculate the absolute value of daily deviations in temperature anomaly as follows:

$$|\text{TA}s, [d, m, y]| = |Ts, [d, m, y] - \overline{T}^{[y-25,,y-1]}_{s,[d,m]}|. \tag{14}$$

We then aggregate these absolute anomalies at the monthly level, treating any departure from the mean—whether hotter or colder than normal as potentially disruptive. Cuculiza et al. (2025) take a comparable approach, examining the absolute values of a firm-level betas with respect to temperature anomalies. Table B.10 confirms their findings in our setting: there is no evidence that the absolute magnitude of temperature anomalies is contemporaneously associated with firm returns.

Tables B.11 and B.12 report the results of quartile and quintile portfolio sorts based on average deviations in precipitation and average deviations in the wildfire index, respectively. The final rows of each table show that the return spreads between high and low exposure portfolios are not statistically significant. These results suggest that firm performance does not systematically vary with these alternative climate-related weather extremes.

Table B.9: Abnormal returns to portfolios sorted on TA

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to the average deviation of temperature anomalies (TA). Each month t, we sort US states into four or five groups based on their realization of TA. Firms headquartered in these states are assigned to the corresponding portfolios, and their returns are value-weighted and rebalanced monthly. Portfolio 1 includes firms operating in states experiencing the lowest values of TA (cold states). Portfolios 4 or 5 include firms in states experiencing the highest values of TA (warmer states). Middle portfolios are grouped together by equal-weighting their returns and denoted as either "Portfolios 2,3" or "Portfolios 2,3,4". We report abnormal returns for each portfolio after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. The final row, "Portfolio 1–5" or "Portfolio 1–4", reports the return spread between the least and most exposed portfolios. The sample includes 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 generate more than 73% of their revenues in the US. 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	0.146*	0.130*	0.114	0.066	0.047
	(0.079)	(0.079)	(0.079)	(0.095)	(0.088)
Portfolios 2, 3, 4	0.003	-0.043	-0.043	-0.122	-0.107
	(0.078)	(0.050)	(0.052)	(0.065)	(0.055)
Portfolio 5	0.032	-0.016	-0.033	-0.112	-0.056
	(0.135)	(0.104)	(0.110)	(0.112)	(0.100)
Portfolio 1 - 5	0.113	0.146	0.147	0.178	0.103
	(0.147)	(0.135)	(0.138)	(0.159)	(0.142)

Table B.10: Abnormal returns to portfolios sorted on $|TA|$

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to the average absolute deviation of temperature anomalies ($|TA|$). Each month t, we sort US states into four or five groups based on their realization of $|TA|$. Firms headquartered in these states are assigned to the corresponding portfolios, and their returns are value-weighted and rebalanced monthly. Portfolio 1 includes firms operating in states with the lowest values of $|TA|$ (temperature closest to the historical average). Portfolios 4 or 5 include firms in states with the highest of $|TA|$ values (more extreme or unusual temperature). Middle portfolios are grouped together by equal-weighting their returns and denoted as either "Portfolios 2,3" or "Portfolios 2,3,4". We report abnormal returns for each portfolio after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. The final row, "Portfolio 1–5" or "Portfolio 1–4", reports the return spread between the least and most exposed portfolios. The sample includes 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 generate more than 73% of their revenues in the US. 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	0.146**	0.136*	0.121*	0.094	0.097
	(0.070)	(0.071)	(0.069)	(0.075)	(0.069)
Portfolios 2, 3	0.035	-0.013	-0.014	-0.089	-0.103
	(0.084)	(0.046)	(0.047)	(0.051)	(0.051)
Portfolio 4	0.029	-0.014	-0.027	-0.068	-0.070
	(0.106)	(0.083)	(0.083)	(0.083)	(0.081)
Portfolio 1 - 4	0.117	0.150	0.149	0.162	0.168
	(0.127)	(0.117)	(0.116)	(0.125)	(0.118)

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 B.11: Abnormal returns to portfolios sorted on deviations in mean precipitation

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to the average deviation of precipitation anomalies. Each month t, we sort US states into four or five groups based on their realization of average precipitation. Firms headquartered in these states are assigned to the corresponding portfolios, and their returns are value-weighted and rebalanced monthly. Portfolio 1 includes firms operating in states experiencing the lowest values of precipitation (lower abnormal rainfall). Portfolios 4 or 5 include firms in states experiencing the highest values of precipitaion (higher abnormal rainfall). Middle portfolios are grouped together by equal-weighting their returns and denoted as either "Portfolios 2,3" or "Portfolios 2,3,4". We report abnormal returns for each portfolio after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. The final row, "Portfolio 1–5" or "Portfolio 1–4", reports the return spread between the least and most exposed portfolios. The sample includes 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 generate more than 73% of their revenues in the US. 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 B.12: Abnormal returns to portfolios sorted on deviations in mean wildfire exposure

This table reports average monthly abnormal returns for portfolios sorted by firm exposure to the average deviation of wildfire risk. Each month t, we sort US states into four or five groups based on their realization of average wildfire risk. Firms headquartered in these states are assigned to the corresponding portfolios, and their returns are value-weighted and rebalanced monthly. Portfolio 1 includes firms operating in states experiencing the lowest values of wildfire risk (lower abnormal wildfire risk). Portfolios 4 or 5 include firms in states experiencing the highest values of wildfire risk (higher abnormal wildfire risk). Middle portfolios are grouped together by equal-weighting their returns and denoted as either "Portfolios 2,3" or "Portfolios 2,3,4". We report abnormal returns for each portfolio after controlling for combinations of the Fama-French 3-factor model, liquidity, betting against beta, momentum, and the Fama-French 5-factor model. The final row, "Portfolio 1–5" or "Portfolio 1–4", reports the return spread between the least and most exposed portfolios. The sample includes 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 generate more than 73% of their revenues in the US. 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)