Nailing Down Volatile Temperatures: Examining their Effects on Asset Prices*

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Abstract

We present a statistic to generally represent extremes in the distribution of temperature anomalies and demonstrate its consequences on financial markets. The diverse shocks that our measure portrays are established to be primary drivers of electricity consumption and the weather futures market. We find that this metric is a significant factor in the cross-section of equity returns in specific industries. A spatial hedging strategy is developed to account for differentially exposed firms to temperature extremes, resulting in a large market-adjusted alpha for the least vulnerable firms. We end by explicitly investigating whether the price reaction to extreme temperatures results from firm operations or investor attention. In each step of our exercise, we contrast our measure with average temperature anomalies and demonstrate that our metric is the first-order feature.

Keywords: Climate Change, Temperature variability, Temperature anomalies, Stock market, Climate news attention.

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

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1 Introduction

Financial markets respond to temperature extremes, but not all shocks are equal. The equilibrium price of an asset can be affected by changes in temperature due to an adjustment in investors' beliefs (Choi et al. (2020)) or directly through firm-level exposure to temperature (Addoum et al. (2021)). Others find a tenuous relationship between temperature fluctuations and financial outcomes (Addoum et al. (2020)). According to the scientific evidence, the probability distribution of temperature anomalies has increased by more than one standard deviation due to climate change since the 1950s (Hansen et al. (2012)). Additionally, the distribution has broadened, leading to a higher number of temperature extremes experienced globally. Identifying a relevant representation of changes in temperature distributions is thus an important aspect of fully understanding changes in temperature extremes, and their associated impacts on financial and economic outcomes.

To characterize extremes in temperature, we create a spatially dependent statistic that reflects deviations in temperature variability from its historical mean, on a rolling basis. The measure, TD-VAR, describes the unconditional distribution of temperature, which allows for the general description of spatial changes in temperature extremes over time. The generality in characterizing extremes with TD-VAR means that we are able to treat cold spells as equally harmful to economic activity as heatwaves. Additionally, we incorporate large fluctuations in day-to-day temperature volatility with the same reasoning. Crucially, through a battery of validation exercises and asset pricing tests, we assert that changes to historical temperature variability is a primary driver of financial markets. We continue our analysis by explicitly disentangling *how* TD-VAR affects markets by investigating whether the shock directly impacts investors' concerns about climate change or firms.

Throughout the paper, we contrast our methodology with existing literature that highlights abnormal temperatures (Addoum et al. (2020)), defined as the number of days in which temperatures exceed a threshold, sustained over a certain time period, causing an extreme temperature event. We define this broadly as a *temperature anomaly* or TD. Addoum et al. (2020), Pankratz and Schiller (2021), and Choi et al. (2020) focus on one side of temperature anomalies – heatwaves – and are reliant on thresholds to define salient extremes. Others, such as Addoum et al. (2021), account for both cold and warm anomalies, yet still use a form of a priori thresholding. We construct TD-VAR to reflect the volatility or variability in temperatures, which is known to affect crop yields (Wheeler et al. (2000), Ceglar et al. (2016)), human health and mortality (Zanobetti et al. (2011)), economic growth (Donadelli et al. (2017), Kotz et al. (2021)), and asset prices (Makridis (2018)).

We construct $\widetilde{TD}$, the realized monthly anomaly, to serve as a counterpoint to TD-VAR. To build both metrics, we utilize multiple geospatial temperature data sets. The first covers city-level temperature data from the U.S. National Oceanic and Atmosphere Administration. The second is a gridded 1-degree latitude by 1-degree longitude daily temperature data set from Berkeley Earth Surface Temperatures (BEST). After aggregating the data to the U.S. state and country levels, we illustrate the differences between TD and TD-VAR with a set of realistic theoretical examples at the monthly and daily frequency. The two measures are then compared and contrasted in each step of our validation and asset pricing exercises, gradually leading to the conclusion that $TD\text{-}VAR$ is the salient measure.

Our validation exercises begin by confirming that deviations in temperature variability are a primary driver of energy consumption and prices in weather derivatives. Following the logic that energy consumption is sensitive to deviations in temperature variability, we perform a time-series analysis connecting the seasonality of energy demand to the two metrics. The analysis produces positive significant coefficients for $TD\text{-}VAR$ on aggregate energy demand, especially in the residential and industrial sectors. In contrast, temperature anomalies only result in a significant positive coefficient for the commercial sector – attributable to the sector's steady energy demand. We continue to substantiate our claims by testing the relationship of the two statistics to the Chicago Mercantile Exchange (CME) weather futures market, which is intrinsically connected to energy consumption. The combined evidence strongly suggests that fluctuations in temperature variability from its historical mean is a first-order factor in the highly related energy and weather futures market.

Next, we test whether the differential exposure of firms to temperature shocks affects the valuation of their stock price. The primary source of variation in our two asset pricing tests are TD and $TD\text{-}VAR$ for a firm headquartered in a U.S. state. Our first set of tests includes monthly cross-sectional return regressions to test the materiality of both temperature factors on Russell 3000 firms. The results indicate that both metrics are insignificant when considering firms in aggregate, corroborating the findings of Addoum et al. (2020). However, we find a positive significant coefficient for $TD\text{-}VAR$ in the energy, utilities, consumer staples, and consumer discretionary sectors. The energy and utility sectors are again affected by temperature variability, reinforcing our validation exercises. A simple explanation for the consumer-related sectors is that shopping is difficult during cold spells or heatwaves, consistent with consumer demand and labor productivity channels (Starr (2000) and Griffin et al. (2017)) and documented in Donadelli et al. (2020), Colacito et al. (2019), Pankratz and Schiller (2021), and Addoum et al. (2021). Average monthly anomalies, on the other hand, are only economically consequential for the utilities sector. The return patterns are robust when we adjust the sample size to various sub-periods.

We continue to test whether investors are pricing deviations in temperature variability by implementing a dynamic investing strategy which goes long on firms headquartered in states that are least affected, and going short on those headquartered in the most-affected states. We build monthly quintile portfolios by ranking states on their exposure to the temperature metrics and place Russell 3000 firms in the differentially exposed portfolios based on their headquarter location. We rebalance the portfolios monthly, depending on the states' exposure to a temperature statistic. The methodology retrieves a time series of portfolio returns which we market-adjust with the Fama-French three factors and an additional momentum factor akin to Barber and Odean (2008). This strategy results in a 50% market-adjusted return over the 14-year sample period when using $TD\text{-}VAR$, compared to a negligible 8% (equivalent to 0.05% monthly) for temperature anomalies when considering all firms. Sectorally, the returns are markedly more for the energy and utilities sectors and are minor for the consumer sectors when using deviations in temperature variability. The results remain robust when we remove firms in states that are continually exposed to temperature shocks. The findings suggest that investors do account for temperature extremes by dynamically hedging the risks.

The aggregate results point to the fact that $TD\text{-}VAR$ is a salient physical risk for financial markets; however, the evidence we present is the combined effect of the material impact on firm operations and investor attention to climate change or temperature. Temperature shocks have an impact on the attention of investors (Choi et al. (2020); Alekseev et al. (2021); Pastor et al. (2021)) and a corporation's earning processes (Addoum et al. (2021)), which together affect the equilibrium price of an asset. We attempt to explicitly disentangle the two effects by first associating the temperature metrics to *innovations* in attention indices, and second by extracting the *true* physical exposure of the firm, divorced from investor attention.

We investigate the attention channel at the U.S. country– and state level after aggregating the temperature metrics to the respective granularity. We adopt the innovations of *The Wall Street Journal* (WSJ) news index from Engle et al. (2020), which captures media coverage of climate change tailored to investors. This index only captures investor attention indirectly, as investors may not necessarily read the news, but we expect that temperature shocks would alert the media and investors to the negative implications of climate change. Additionally, we acquire the innovations of Google Search Volume Index (SVI) data at the state level for the topics "Climate Change" and "Temperature". Using this data, we explore whether retail investors react to localized temperature shocks (Alekseev et al. (2021)). Our U.S.-level results show a moderately significant relationship between $TD\text{-}VAR$ and unexpected news in the WSJ index. Similarly, there is a strongly significant relationship between our metric and both search topics. The only discernible relationship for temperature anomalies in both exercises is a positive significant relationship to searches for "Temperature". Collectively, the results suggest that shocks to temperature variability act as a "wake-up call" for investors.

The final exercise is to measure the attention-adjusted firm-level impact of temperature shocks. Due to data constraints and for reasons of simplicity, we assume that a firm's operations will be affected in the same state as their headquarters. If a temperature shock is truly salient to the processes of a firm, analysts will raise the issue of physical risk during earnings conference calls. We obtain a measure of firm-level exposure to physical risks from Sautner et al. (2020) who capture the pertinent discussion from earnings calls. Their measure, however, is influenced by attention to climate change as seen by their positive association with the WSJ index. To disentangle this effect, we obtain residuals from a regression of expected and unexpected news from the WSJ on their physical exposure series. The residuals, which we call NetExposure, can be considered the 'true' impact of physical risks on a firm. We find that elevated $TD\text{-}VAR$ is significantly positively associated with an increase in NetExposure of a firm in comparison with $\widetilde{TD}$. Additionally, we find much larger effect sizes for the utilities and energy sector with our metric. Similar to our prior exercises, we find a muted effect on consumer sectors. In total, the results contextualize the price reaction by showing that $TD\text{-}VAR$ is salient for investors and firm operations.

Our primary contribution is to the nascent research on the financial consequences of temperature. Most work on climate shocks and financial markets defines abnormal temperatures as temperature extremes, i.e. temperatures being above a certain threshold, and investigates its effects on the international food industry (Hong et al. (2020)), firm earnings or profits (Pankratz and Schiller (2021); Addoum et al. (2020)), futures markets (Schlenker and Taylor (2021)), or asset prices in general (Bansal et al. (2017)). Addoum et al. (2021)

incorporates the effects of both cold spells and heatwaves on industry earnings. One more relevant paper is that of Donadelli et al. (2017) who primarily investigate the effect of temperature volatility on macroeconomic outcomes and also find that shocks diminish U.K. and European equity prices in the cross-section.

We extend this literature in a number of ways. Our metric describes changes in the distribution of temperature anomalies, which reflects extremes more comprehensively than thresholds do. We document that deviations in temperature variability can represent extreme temperatures in a way that is salient for both weather futures and stock markets. While Addoum et al. (2021) focus on earnings, our results are in line with their findings that markets react both to extremely hot and extremely cold days. Furthermore, we find that day-to-day swings in temperature are similarly consequential for the same markets. Our study also expands the equity pricing tests of anomalies in temperature volatility of Donadelli et al. (2017) in concrete manners: (1) by directly validating the importance of deviations in temperature variability in the energy consumption and weather futures market; (2) performing an asset pricing factor analysis to examine the relationship between deviations in temperature variability and U.S. stock returns; and (3) developing a long–short strategy to explore investor reactions to sub-national heterogeneity in temperature in the U.S. equity market.

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

This paper is organized as follows. Section 2 describes the data and explains our data set construction procedure. Section 3 describes how we expand upon prior temperature statistics and derive $TD\text{-}VAR$, the deviation in temperature variability. This section also illustrates that $TD\text{-}VAR$ comprehensively quantifies the extremes in the distribution of temperature. Section 4 validates $TD\text{-}VAR$ using electricity consumption and weather derivatives. The investigation into the relationships between $TD\text{-}VAR$ and the U.S. equity market follows in Section 5. Section 6 disentangles the effect of $TD\text{-}VAR$ on investors' attention and isolates its direct impact on firms. Section 7 concludes.

2 Data

In this work, we consider data from a variety of sources. We start with geospatial temperature data that have a temporal characteristic. We link the spatial feature to financial variables by extrapolating their location. Finally, attention indexes are aggregated at national and sub-national levels.

2.1 Temperature data

Our analysis is based on the conjecture that deviations in temperature variability are more likely to affect the profitability of the U.S. corporate sector than are changes in mean temperature. The effects associated with deviations in temperature variability are likely to vary substantially across time and location.

We collect data to test the relationship between deviations in temperature variability and weather derivatives. In particular, we obtain city-level temperature data for 13 U.S. cities[1] using the U.S. National Oceanic and Atmosphere Administration (NOAA) repository. Specifically, we use the NOAA Global Historical Climatology Network daily (GHNCd), an integrated database of climate summaries from land surface stations across the globe. For each city, we select the station corresponding to the closest city airport and retrieve the daily maximum temperature from the GHNCd.[2] The temperature data cover the period from 1 January 1950 to 31 December 2021. We pre-process the data by filling in missing values with the average of the maximum temperature recorded on the days either side. Table 1 reports the cities in our data set, the GHNCd code, the mean daily temperature, and the corresponding standard deviation.

The majority of our empirical analysis requires a spatially uniform, rather than city-specific, estimate of temperature. To measure location-specific exposure, we obtain spatially homogeneous daily temperature from the BEST database.[3] The BEST data are in the form of gridded 1-degree latitude by 1-degree longitude reconstruction of daily temperatures. BEST spatial interpolation provides extensive spatial coverage from 1950 to the present. BEST utilizes data from significantly more land stations (over 40,000) than the 10,000 used by alternative data sets, improving the assessment of record-setting daily U.S. temperatures. The data is then used to compute state-level and U.S.-wide daily temperatures, the details of which are presented in Section 3.4 and Appendix A.1.

2.2 Financial and economics data

We collect data on returns for the Russell 3000, an index tracking the performance of the 3,000 largest U.S. companies, representing approximately 97% of the investable U.S. equity market.

[1]These are: Atlanta, ATL; Boston, BOS; Baltimore Washington, BWI; Chicago, ORD; Cincinnati, CVG; Dallas Fort Worth, DFW; Des Moines, DSM; Detroit, DTW; Las Vegas, LAS; Minneapolis St Paul, MSP; New York, LGA; Portland, PDX; Philadelphia, PHL; Salt Lake City, SLC, and Tucson, TUS. This same data was used in Diebold and Rudebusch (2019).

[2]Later in the analysis, we consider temperature-related weather derivative instruments. These contracts are city-specific and are settled based on the temperature readings of a specific weather station near the contract city.

[3]The application of homogenization techniques to daily temperature data is important in order to accurately understand the evolution of temperature extremes over the past century. The BEST daily temperature data use of a novel homogenized gridded approach to improve the assessment of record-setting daily U.S. temperatures. We refer to Rohde et al. (2013) and Rohde and Hausfather (2020) for a technical discussion.

Data on Russell 3000 constituents, their firm fundamentals and headquarter locations are drawn from Refinitiv, and they are classified into their respective sectors using the Global Industry Classification Standard (GICS).

In Table 2 we report summary statistics on stock returns and several control variables used in our subsequent tests. The dependent variable, $r_{i,t,s}$, in our cross-sectional return regressions is the monthly return of an individual firm i in month t, headquartered in state s. We use the following control variables in our cross-sectional regressions: $LOGSIZE_{i,q}$, given by the natural logarithm of firm i's market capitalization (price times shares outstanding) at the end of each quarter q; $B/M_{i,t}$, which is firm i's book value divided by its yearly market cap; $ROE_{i,t}$, which is given by the ratio of firm i's net yearly income divided by the value of its equity; $LEVERAGE$, which is the ratio of debt to book value of assets; capital expenditures $INVEST/A$, measured as the firm's yearly capital expenditures divided by the book value of its assets; $LOGPPE$, which is given by the natural logarithm of the firm's property, plant, and equipment at the end of year t; $MOM_{i,t}$, which in turn is given by the average of returns on stock i, for the 12 months up to and including month $t-1$.

To assess portfolio exposure to the classical three Fama-French factors, we download the factors from Kenneth French's data repository (French (2020)) for the U.S. equity market. These factors are related to the Russell data set we employ for the financial analysis. Table 3 provides summary statistics on the three factor[4] characteristics: market return minus risk-free rate (Mkt-RF), small minus big (SMB) and high minus low (HML).

We collect data covering September 1990 to December 2020 on electricity consumption and weather futures prices to validate the materiality of our metric. We obtain time-series data on energy demand for 50 U.S. states at the monthly frequency from the U.S. Energy Information Administration. The U.S. classification considers four end-use sectors: residential (homes and apartments), commercial (offices, malls, stores, schools, hospitals, hotels, warehouses, and public assembly), industrial (facilities and equipment used for manufacturing, agriculture, mining, and construction), and transport.

Weather futures contracts are traded on the CME, and a majority of weather contracts are based on temperature. Temperature-related contracts insure the buyers against either excessive heat or excessive cold during a specified period of time. The two main temperature instruments are Heating Degree Day (HDD) contracts and Cooling Degree Day (CDD) contracts. The buyer of an HDD contract receives payments for cold days, defined as days with average temperature below 65°F; conversely, the buyer of a CDD contract receives payments for hot days, defined as days with average temperature exceeding 65°F. Contracts are available for eight geographically distributed cities across the U.S. These contracts are written on the observed temperature at a specific weather station near the contract city for a specific period. We select the same cities considered in Diebold and Rudebusch (2019) and Schlenker and Taylor (2021): Atlanta, ATL; Chicago, ORD; Cincinnati, CVG; Dallas Fort Worth, DFW; Las Vegas, LAS; Minneapolis St Paul, MSP; New York, LGA; and Portland, PDX.[5] Daily futures prices (end of day) for HDD and CDD contracts were obtained from Bloomberg, covering 2005 to 2020.

[4]For a comprehensive description, refer to Fama and French (1993)

[5]Table 1 indicates which of the cities in our larger city sample have temperature derivatives available.

2.3 News and attention index

Concerning news indices, we employ data from several sources. From Google Trends we retrieve the Google Search Volume Index (SVI) from 2004 for a particular topic at the U.S. country and sub-national level.[6] The retrieved monthly index, $G_{s,t}$, represents the intensity of the topic search, on a scale from 0 and 100, in a certain region, s, from 2004 to the present. For each state, 0 represents a month with no searches on the topic whereas 100 is the month with the most searches in its history. Two states may peak at the same time; however,because the scale only compares time periods within a state, two states may have the same index value at the same time, without having the same actual search volumes. We download the Google SVI for the 50 states based on "climate change" and "temperature" search terms. Figure (1) shows the difference between the indices averaged at the U.S. level. We note that searches for "temperature" display a clear seasonal pattern, which we de-trend using the methodology outlined in Choi et al. (2020).

We also use the WSJ news index created by Engle et al. (2020), which captures both physical and transition risks. The series they build is based on the assumption that any news about climate change is bad news. The news index is broken down by month, covering July 2008 through June 2017. When using this index, our sample is truncated to reflect this shortened time period.

2.4 Other data

In order to aggregate the state temperature index at the country level, we employ a population and gross domestic product (GDP) weighting method. We obtain the population and GDP series from the Federal Reserve Economic Database released by the Federal Reserve Bank of St. Louis. Population is available at the state level through the code 'POP', with a starting date of 1950. To match the monthly temperature and financial data sets, we interpolate the yearly frequency of the population data to obtain monthly or daily series. GDP is available through the code 'RQGSP', which returns quarterly real gross product for each state. We perform a similar interpolation method to obtain a monthly or daily series.

We examine firm-level exposure to temperatures by adopting data developed by Sautner et al. (2020). Their physical exposure measure consists of the proportion of time an earnings conference call centers around physical climate shocks. The data is available at a quarterly frequency and runs from 2000 to 2020. When using this measure, we average our temperature and attention data to the quarterly frequency.

3 On the evolution of excess temperature dynamics

Our aim is to represent the spatio-temporal variation in the distribution of temperature anomalies and, in particular, extreme temperatures, in a way which is more salient for financial markets. To do so, we expand upon prior temperature statistics to incorporate a

[6]Google makes the Search Volume Index (SVI) of search terms public via the product Google Trends (`www.google.com/trends`). Weekly SVI for a search term is the number of searches for that term scaled by its time-series average.

more complete representation of abnormal temperatures by gradually building a statistic of temperature variability, named $TD\text{-}VAR$,. With concrete and theoretical examples, we illustrate *why* our statistic is comprehensive in quantifying the extremes in the distribution of temperature. We end the section by describing our aggregation methodology used for our empirical analysis.

3.1 TD–VAR derivation

In the spirit of Donadelli et al. (2019) and Kotz et al. (2021), for a given location, we compute the variability in temperature deviation and subtract this value from its historical mean. This metric effectively captures changes in temperature extremes by means of shifts in temperature variability across time. It has been shown that a high degree of variability in temperature anomalies tends to be associated with more frequent extreme temperature events (Hansen et al. (2012)). Considering that the literature confirms that abnormal temperature anomalies cause economic and financial disruptions, we argue that deviations in temperature variability are a primary driver of market reactions, and this statistic improves upon alternative statistics used in the recent literature, such as changes in mean temperature and abnormal or extreme temperatures (Addoum et al. (2020), Addoum et al. (2021), Pankratz and Schiller (2021)).

To that end, we construct a set of location-specific temperature statistics. First, similar to Kotz et al. (2021), we define the daily change in mean temperature as:

$$TD_{s,d} = (T_{s,d} - \overline{T}_{s,d}), \tag{1}$$

where $T_{s,d}$ indicates the *maximum* temperature observed in location s on a certain day d in the year; and $\overline{T}_{s,d}$ represents the historical average temperature in the same location s and on the same day d over the period 1960–2005. A smoothing window of 5 days is used to calculate the historical average daily temperature.

Then, we define the monthly *temperature anomaly*, $\widetilde{TD}_{s,m}$, as the average of the temperature anomalies relative to the daily mean temperature within a given month. Analytically, this corresponds to:

$$\widetilde{TD}_{s,m} = \frac{1}{D_m} \sum_{d=1}^{D_m} TD_{s,d}, \tag{2}$$

where D_m is the number of days within month m.

Next, we calculate the monthly standard deviation in temperature anomalies in month m:

$$\sigma(TD_{s,m}) = \frac{1}{D_m} \sqrt{\sum_{d=1}^{D_m} TD_{s,d}^2}. \tag{3}$$

Lastly, we calculate the deviation in temperature variability from its historical mean and obtain the *deviation in temperature variability:*

$$TD\text{-}VAR_{s,m} = \sigma(TD_{s,m}) - \overline{\sigma}(TD_{s,m}), \tag{4}$$

where $\overline{\sigma}(TD_{s,m})$ represents the historical average temperature variability recorded in location s at month m.[7] This second term distinguishes us from Donadelli et al. (2019), as their measure captures the dispersion of temperature variability against a historical level observed over the industrial revolution era, i.e. 1659–1759.

We emphasize that $TD\text{-}VAR$ can assume both negative and positive values. A negative value of $TD\text{-}VAR$ corresponds to a tighter distribution of temperature anomalies compared to historical realizations. Consequently, the likelihood of a large anomaly decreases. A positive value of $TD\text{-}VAR$ corresponds to wider variability of temperature anomalies and, by construction, an increase in the unconditional probability of large swings. A positive $TD\text{-}VAR$ can be the result of two distinct and non-concomitant patterns. First, where the temperature deviates strongly in one direction during elongated cold spells or heatwaves. Second, when day-to-day temperatures swing frequently between hotter– or colder-than-normal periods. In the next sections we describe where we observe these patterns in the data. Crucially, statistics that rely on shifts in mean temperature, $\widetilde{TD}$, and abnormal temperature are insufficient for describing changes in the unconditional probability of temperature.

3.2 Intuition on TD-VAR

Now that we have formally derived $TD\text{-}VAR$, we illustrate its ability to describe temperature extremes more comprehensively in comparison to using thresholds. Also, we discuss its advantages and various properties in the context of prior literature. Schlenker and Taylor (2021) and Addoum et al. (2020) use a form of TD by defining extreme temperatures as the number of days in a month where the temperature exceeds a given heat threshold. However, both heatwaves and cold spells can cause severe issues. For example, in early 2021, a winter storm hit Texas causing power cuts and, as lamented by the Financial Times, provoking disruptions to the global supply chain for chemical raw materials.[8] Addoum et al. (2021) correct this by accounting for both warmer and cooler temperatures, yet still use a form of a priori thresholding. When calculating temperature anomalies, thresholds are likely to vary substantially across time and location. $TD\text{-}VAR$ presents the most salient spatio-temporal information, providing a sufficient characterization of the distribution of temperature and concisely describing temperature extremes.

The primary benefit of using our metric versus other temperature measures such as TD, is its ability to capture temperature extremes without introducing idiosyncratic thresholds. Building on the literature that confirms the relationship between temperature anomalies and economic and financial disruptions, we claim that our measure $TD\text{-}VAR$ improves upon $\widetilde{TD}$ in representing noticeable characteristics of temperature anomalies and their economic and financial impacts. We show, through a set of exercises, the relative importance of $TD\text{-}VAR$ over $\widetilde{TD}$ in representing extremes in the temperature distribution.

[7] It is possible to compute an equivalent daily $TD\text{-}VAR$ over a rolling window l. First, we compute the standard deviation in temperature anomalies in location s at day d observed over the past l days: $\sigma(TD)_{s,d,l} = \frac{1}{l}\sqrt{\sum_{i=1}^{l} TD^2_{s,d-i}}$. Then, we compute the $\overline{\sigma}(TD_{s,d,l})$, the historical average temperature variability recorded in location s at day d with lag l. We then obtain the daily $TD\text{-}VAR$ defined as $TD\text{-}VAR_{s,d,l} = \sigma(TD_{s,d,l}) - \overline{\sigma}(TD_{s,d,l})$

[8] The Financial Times, March 24th, 2021 - "Global supply chains face months of disruption from Texas storm"

We begin with a real-world example of occurrences of extreme temperatures and the average value of monthly temperature anomalies, $\widetilde{TD}$. Figure 2 represents the temperature conditions in Boston during the year 2020. The red bars represent the number of days that Boston experienced an 'extreme' temperature – defined as a temperature that exceeds 1.5 times the historical standard deviation. The blue line is the average monthly temperature anomaly, $\widetilde{TD}$. In January, the average temperature anomaly is substantial, but the frequency of extremes is low. The average temperature anomaly over December and April is modest but there is a high number of extreme days. In aggregate, the results show that a measure based on average anomalies does not adequately reflect the frequency with which a location experiences extreme temperatures.

We now turn to a theoretical example to illustrate why thresholds fail to represent temperature extremes. We consider a continuous response variable x characterized by a probability density function $\psi(x)$. The probability of experiencing an extreme value, X_{TD} is computed using the area above or below the thresholds k_{max} and k_{min}, which represent the values associated with the definition of an extreme.[9] Analytically, X_{TD} can be expressed as:

$$X_{TD} = \int_{k_{max}}^{\infty} \psi(x)dx + \int_{-\infty}^{k_{min}} \psi(x)dx, \tag{5}$$

where $\psi(x)$ is the probability density function of TD.

The two components we define, $\widetilde{TD}$ and $TD\text{-}VAR$, characterize shifts in the distribution parameters of TD. In the absence of climate change, $\widetilde{TD}$ is equal to 0, as is $TD\text{-}VAR$. Changes in $\widetilde{TD}$ represent the differences in the average realization of the temperature distribution; however, a positive $\widetilde{TD}$ does *not* imply an increase in the occurrence of extremes. In contrast, changes to $TD\text{-}VAR$ modify the entire shape of the distribution of TD, explicitly increasing the variability and the probability of extreme temperatures.
Simply put, changes in $\widetilde{TD}$ characterize shifts in the mean of TD while $TD\text{-}VAR$ accounts for a change in the variance of TD.

To continue our theoretical example, we present conceptual arbitrary thresholds typically used to represent temperature extremes. We assume that TD exhibits a normal distribution characterized by the parameters μ, which is set to zero, and σ^2 is set to the historical unconditional variance of TD.[10] Further, $\overline{\sigma}^2$ is fixed to 25 which is in line with the unconditional historical temperature data. Finally, we set k_{max} to 10°F and k_{min} to -10°F. In this baseline scenario, the amount of time a location experiences an "extreme" temperature is 4.6%, or 1 day in a month.

As there is no closed formula to formally calculate the amount of time spent above or below each threshold, we present a simulation that describes the interactions between the values of $\widetilde{TD}$ and $TD\text{-}VAR$.
Figure (3) shows the extreme probability, represented by the red shaded area for differing values of $TD\text{-}VAR$ and $\widetilde{TD}$. The central reference graph represents the historical distribution of temperature anomalies characterized by mean zero and the historical average volatility level. The historical average volatility level also implies that $TD\text{-}VAR$ is zero. Moving

[9] This definition of temperature extremes is closely related to Pankratz and Schiller (2021), Addoum et al. (2020), and Addoum et al. (2021).

[10] μ equal to zero is a case where there is no global warming.

horizontally or vertically from the central plot represents nominal changes in $\widetilde{TD}$ and TD-VAR, respectively. The right column, where the temperature anomaly has a positive value, is associated with an increase in the occurrence of extremes *only* when TD-VAR is non-negative. In contrast, positive values of TD-VAR – in the first row – are always associated with a larger shaded area, even in the case of negative values of $\widetilde{TD}$. These instances illustrate the drawbacks of solely using $\widetilde{TD}$ rather than TD-VAR. In sum, using only the average of TD fails to consider potentially salient temperature realizations which TD-VAR can better capture.

In the prior examples, we assumed TD-VAR and $\widetilde{TD}$ to be independent when assessing TD-VAR's relative importance from various theoretical perspectives. Here, we demonstrate how TD-VAR correlates with other temperature measures. Table 4 shows the long-term relationship of TD-VAR with other temperature factors, such as levels, deviation and variability. As already presented, there is no linear relationship between temperature anomalies and temperature levels. Deviation variability, however, shows a negative correlation coefficient of -0.8 due to the fact that variability is higher in winter and lower in summer, a fact well documented in the literature. When we turn our attention to TD-VAR, we note the negligible positive relationship with these other variables. We highlight that TD-VAR does not display a seasonal pattern as the variability, and the relationship with variability, is absent.

Fundamentally, our examples highlight that temperature extremes can be better characterized using deviations in temperature variability. A key aspect of this argument is that it obviates the need for thresholds. We extend our theoretical explanation of the advantage of TD-VAR over TD with realistic examples in the following sections.

3.3 City-level evidence

In this section, we supplement the prior theoretical examples with real-world, city-level records of TD-VAR and $\widetilde{TD}$. We compute each value for 13 U.S. cities to further demonstrate the key differences between the two measures, analogous to Diebold and Rudebusch (2019). We select periods of time in these cities to graphically represent the temperature and temporal dynamics of its derivations. Furthermore, we highlight important differences after aggregating temperature data to the state level.

We obtain daily maximum temperature data from NOAA as our basis for our various offshoot measures. This data, from 1950 onward, are recorded at the airport stations of the 13 cities.[11] From the daily maximum level, we extract temperature, T, temperature anomalies, TD, temperature variability, $\sigma(TD)$, and deviation in temperature variability, $TD - VAR$. The former two metrics are defined at a daily frequency while the latter two are computed on a 30-day rolling window. Figure 4 displays the plots of these four statistics for the city of Atlanta between 2016 and 2018. Unsurprisingly, temperature T is characterized by seasonal changes, as illustrated in the top left diagram.

The random variable TD, shown in the top right panel, is generated after adjusting tem-

[11] These temperature stations are the same as those used to compute the value of the temperature derivative contracts in Section 4.

perature for seasonality.[12] This component exhibits a slow-moving long-term trend, shown in red, which represents the average warming due to carbon emissions. During the winter months, temperature anomalies are highly volatile compared to the summer months. The seasonality of TD volatility is made clear in the bottom left plot by calculating $\sigma(TD)$ using Equation 3. Lastly, deviations in temperature variability are derived in the bottom right diagram after removing the long-term seasonality/variability component. TD-VAR improves upon TD by removing the sluggish rise in temperatures and the seasonality component.

To further contextualize the plots in Figure 4, we explore the difference between TD-VAR and TD by highlighting one particular city location: Boston. We perform a rolling computation of $TD - VAR$ and TD at the daily level for a time window of 2015 through 2018, shown in Figure 5. The top and bottom panels of the figure contain the realizations of TD and TD-VAR, respectively. We exemplify a few moments in time to more realistically describe a link between TD and $TD - VAR$. There are three particular peaks in $TD - VAR$ for the city of Boston: June–July 2015, February–April 2016, March–April 2017. For the first peak, we note that TD is persistently high, portraying a heatwave, in comparison with the historical average – shown in red – during these months. The second peak of TD-VAR is related to large swings of temperature anomalies in both directions. The final high variability temperature event, beginning in March 2017, exhibits both persistently higher deviations and fluctuations around the historical average value. Combined, these instances show no direct link between the two measures at the daily level, which is corroborated by Table 4, as the correlation coefficient between $TD - VAR$ and TD is 0.12. To clarify the true disconnect between the two measures, we aggregate the values to the state level.

Figure 6 highlights the differences between the two temperature measures after deriving the monthly $TD - VAR$ and $\widetilde{TD}$ – Equation(2, 4) – for the state of Texas. In the right panel of Figure 6, we plot monthly anomalies relative to historical temperatures, $\widetilde{TD}$, whereas the left panel illustrates the monthly deviation in temperature variability, TD-VAR. In May through June of 2018, there are high values of $TD - VAR$ in comparison to $\widetilde{TD}$, which is reversed in the months between October and December of 2019. This selected example illustrates that higher levels of TD are not tied to higher levels of TD-VAR, as the two metrics capture different aspects of the temperature distribution.

3.4 State and country aggregation

For our empirical analysis in the next sections, we use aggregated measures of TD-VAR and $\widetilde{TD}$ to represent the spatio-temporal heterogeneity of temperature. Our underlying assumption is that firms and investors react to temperature shocks which are inherently local. We first aggregate gridded temperature anomalies to the state level because there is prior evidence that investors react to local weather shocks (Choi et al. (2020)). Additionally, due to data constraints and for reasons of simplicity, we assume that a firm's operational footprint is primarily located in the same state as its headquarters. To match country-level indices for our empirical analysis, we also combine the state-level aggregations.

[12]Here, TD is comparable to measures in Pankratz and Schiller (2021), Addoum et al. (2020), and Schlenker and Taylor (2021). A caveat is that Pankratz and Schiller (2021) and Addoum et al. (2020) only use heatwaves.

We begin by computing state-aggregated temperature. We collect grid-level data from the BEST, which assigns a temperature field at a 1-degree resolution within U.S. land borders. The aggregation method can be formally defined by the temperature T of state s on day d as follows:

$$T_{s,d} = \sum_{i=1}^{N_s} w_i * T_{i,d}, \tag{6}$$

where $T_{s,d}$ is a weighted average of the temperature assigned to each grid cell $i = 1, \ldots, N_s$, and N_s is the number of parcel grids cells. We equally weight the cells by setting the weights w_i equal to $1/N_s$, which allows for a consistent measurement of average maximum temperatures at the state level. This methodology allows us to derive $\widetilde{TD}$ and $TD\text{-}VAR$ of state s as described in expressions (1), (3), and (4). Our process of obtaining sub-national temperature data is similar to other papers such as Burke and Tanutama (2019). In Appendix A.1 we discuss alternative aggregation methods.

To derive U.S.-wide temperature factors, we aggregate each temperate volatility measure from its state counterpart. Aggregating data to the country level subsumes the rich sub-national heterogeneity of temperature data but allows us to match it to other country indices and data sources. We strictly define U.S.-wide $\widetilde{TD}$ and $TD\text{-}VAR$ as follows:

$$US_{\widetilde{TD},m} = \sum_{i=1}^{N_s} w_i TD_{i,m}, \tag{7}$$

$$US_{TD-VAR,m} = \sum_{i=1}^{N_s} w_i TD\text{-}VAR_{i,m}. \tag{8}$$

While there are multiple ways to aggregate temperature data, we consider each state to be its own grid cell.[13] The measure for each state is then equally weighted by setting $w_i = 1/50$. In Appendix A.1 we discuss possible alternatives, such as weighting for the resident population or the GDP of a specific state.

4 Validation using electricity consumption and weather derivatives

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

[13] Expressions (18) and (19) in Appendix A.1 describe alternative methods.

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

$$Q_{s,t} = \sum_{j=1}^{J} a_j Q_{t-j} + \sum_{p=1}^{P} b_p \epsilon_{t-p} + \epsilon_{s,t} \tag{9}$$

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

$$\epsilon_t = \beta_v * TD\text{-}VAR + \beta_t * \widetilde{TD} + \gamma_t + \eta_n + \epsilon. \tag{10}$$

Table (6) shows the resulting coefficients. We observe a positive and statistically significant β coefficient for the deviation in temperature variability, $TD\text{-}VAR$, in residential and industrial sectors and in the aggregate. A positive coefficient implies that, in a month characterized by high variability, the forecast value of electricity consumption exhibits a larger error relative to the best-fit value estimated through Equation (9). This error is inherently determined by the extent of the variability. The non-significant coefficient for $TD\text{-}VAR$ in the commercial sector suggests that the elasticity of electricity consumption is different for the residential and commercial sectors. This conclusion is supported by Zachariadis and Pashourtidou (2007) who find that the residential sector is highly reactive to weather conditions, as demand in the short term is inelastic to price. Taken together, our results confirm prior evidence of energy consumption being highly affected by weather conditions (Quayle and Diaz (1980)) and sensitive to large shifts in temperature variation. (Chang et al. (2016)).

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

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

$$
\begin{aligned}
CDD_{i,m} &= \textstyle\sum_{d=1}^{D_m}(T_d - T_0, 0)^+ \\
HDD_{i,m} &= \textstyle\sum_{d=1}^{D_m}(T_0 - T_d, 0)^+.
\end{aligned} \tag{11}
$$

We use ordinal least square (OLS) regression analysis to investigate whether monthly average prices for CDDs and HDDs are affected by temperature – measured as temperature deviation and deviation in temperature variability. We estimate CDDs and HDDs separately with the following equations:[14]

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

where T_m is the average daily temperature level minus 65°F degrees and $\widetilde{TD}$, $\sigma(TD)$, and $TD\text{-}VAR$ are defined in Section (3.1). For month and state fixed effects, we include γ_m and η_s, respectively. We only consider the constant term in winter given that the contract is not written on the maximum temperature of 65°F. We split the contract data into winter (October to March, inclusive) and summer months (April to September, inclusive).

Table 5 shows the results for the two contracts using various temperature drivers. The first column of each panel includes the underlying temperature on which the contract is written, while the second column includes the other volatility measures. We show that T_m alone is able to explain 90% of monthly average price variance for CDDs in summer and 95% for HDDs in winter. An increase in temperature results in a decline in the price of CDDs, and vice versa for HDDs. Unsurprisingly, the magnitude of the coefficients is similar and of opposite sign, given that the derivative is dependent on the deviation from the 65°F threshold.

We then consider the remaining statistics: $TD\text{-}VAR$, $\widetilde{TD}$, and $\sigma(TD)$. We document that historical variability, $\sigma(TD)$, has a large significant coefficient during the winter but no effect in summer. The result supports the findings in prior literature that temperature volatility is greater during these months.[15] The coefficients for $TD\text{-}VAR$ are comparable across winter and summer, which is intuitive when recalling the option price effect of the volatility on the underlying asset. Higher deviations in temperature variability from the historical mean increase the probability of experiencing extreme temperatures and, consequently, increase the probability of exercising the option, thereby increasing the value of the weather derivative contract. This indicates that two cities with comparable average temperatures may face diverging weather derivatives prices when one city is characterized by higher temperature variability. Finally, we compare the coefficients of TD which have signs in the opposite direction to T_m. This suggests that traders assume temperatures will revert back to their historical levels when a city experiences higher temperature deviations. Collectively, we

[14]We use the derivatives defined in Section 3.3, and only consider the seven cities for which the derivatives are still traded.

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

find that traders react negatively to increasing $TD\text{-}VAR$ by establishing a higher price for the apparent risk, whereas an increase in TD implies a reversion to the mean for the market.

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

5 Empirical analysis

5.1 Estimating temperature exposure

We analyze the effect of temperature deviation $\widetilde{TD}$ and deviations in temperature variability $TD\text{-}VAR$ on firm stock prices. Specifically, we are interested in examining whether the differential exposure of firms to deviations in temperature and temperature variability affect their stock price. Our expectation is that $TD\text{-}VAR$ will be associated with a collective reaction from investors as well as material shocks to a firm's performance, resulting in an aggregate decline in a firm's stock price. To empirically test this we use the Russell 3000, a broad index covering 3,000 major U.S. firms, and collect data on firm stock returns and headquarter locations. This framework benefits from the panel data characteristics of our sample, which is rich in both the cross-section and time-series dimensions. Moreover, it is possible to investigate the temperature dynamics at the industry level and include time– and firm fixed effects. We do not employ geography fixed effects since geographical differences are captured by the state-level temperature.

Table (2) in Section 2 provides summary statistics on stock returns and several control variables used in our analysis. The dependent variable, $r_{i,t,s}$, in our cross-sectional return regressions is the monthly return of an individual firm i in month t and headquartered in state s. We use the following control variables in our cross-sectional regressions: $LOGSIZE_{i,q}$, given by the natural logarithm of firm i's market capitalization (price times shares outstanding) at the end of each quarter q; $B/M_{i,t}$, which is firm i's book value divided by its yearly market cap; $ROE_{i,t}$, which is given by the ratio of firm i's net yearly income divided by the value of its equity; $LEVERAGE$, which is the ratio of debt to book value of assets; capital expenditures $INVEST/A$, measured as the firm's yearly capital expenditures divided by the book value of its assets; $LOGPPE$, which is given by the natural logarithm of the firm's property, plant, and equipment at the end of year t; $MOM_{i,t}$, which in turn is given by the average of returns on stock i, for the 12 months up to and including month $t-1$. To allow for systematic differences in correlations across firms and over time, we include firms fixed effects η_t and year–month fixed effects ϕ_t. In this regard, our identification comes from states' variation in a given month.

In turn, we consider the effect of abnormal temperature, measured as the average daily temperature deviation within a month ($\widetilde{TD}$), and the effect of abnormal temperature variability, measured as the deviation in temperature variability from its historical mean in the same month ($TD\text{-}VAR$). This regression captures the impact of temperature on stock returns at the state level. Taking both abnormal temperature and abnormal temperature variability into account, we believe this measure provides a rough proxy for the climate change risk that a firm is exposed to at a given point in time.

Specifically, we estimate the following model:

$$r_{i,t,s} = \alpha + \beta_T * T_{t,s} + \beta_1 C_{i,t-1} + \phi_t + \eta_i + \epsilon_{i,t} \tag{13}$$

where $r_{i,t,s}$ measures the stock return of firm i in month t and headquartered in state s. T is a generic term that can stand in for either the deviation of daily temperature from its historical mean within a month ($\widetilde{TD}$), or the deviation of daily temperature variability from its historical mean in the same month ($TD\text{-}VAR$). The vector of firm-level controls C includes the firm-specific variables described earlier. We estimate these two cross-sectional regressions using panel OLS. In both model specifications, we cluster standard errors at the firm and year levels, which allows us to account for any serial correlation in the residuals and to capture the fact that some control variables are measured at an annual frequency.

We begin our analysis by asking whether temperature exposure affects the stock returns of Russell 3000 firms. Table 7 presents distinct estimates of the effect of abnormal temperature, Panel A, and abnormal temperature variability, Panel B. Specifically, once we control for firm and time period, as well as a battery of firm characteristics, the estimated effect of temperature deviation $\widetilde{TD}$ is economically small and statistically insignificant when considering all firms (first column of Panel A). Nor do we find evidence of a significant relationship between an average firm's exposure to deviations in temperature variability, $TD\text{-}VAR$, and its stock returns (first column of Panel B).

Our empirical tests thus far indicate that exposure to temperature deviation and deviations in temperature variability has a minimal effect on stock returns for the *average* firm in the Russell 3000. To this point, our findings substantiate the results of Addoum et al. (2020), who document that temperature exposure is not an important driver of establishment-level sales growth. These findings are consistent with those of Dell et al. (2012), who show that the negative effects of temperature on aggregate economic growth are concentrated among developing countries, but tenuous in richer economies.

While there is some evidence that extreme temperatures have no effect (Addoum et al. (2020)), certain sectors of the economy may still exhibit sensitivity to abnormal temperatures. As such, we continue our analysis to examine whether firms in certain economic sectors are particularly sensitive. We use GICS codes to organize Russell 3000 firms into 10 sectors. In Table 7 Panel A, we rerun our yearly stock return regression for each sector. For all sectors except utilities (electric utilities; gas utilities; and multi-utilities), we continue to find economically and statistically insignificant estimates associated with exposure to temperature deviations. Months that are warmer or colder than expected are equally good and bad for all these industries. Utilities are a special case though, because they are tasked with providing enough energy over time as well as meeting instantaneous electricity demand, while juggling the costs associated with grid balancing and a continuous expansion of non-dispatchable renewable generation. As such, deviations in average daily temperature require utilities to invest more in emergency measures, such as increasing capacity and expanding demand–response investments to mitigate the effects of unexpected changes in daily temperatures. Accordingly, our analysis reflects that the effect of abnormal temperatures on utilities is economically important. The estimate indicates that deviations of the daily temperature from the historical mean are associated with a 10.04 percentage-point decrease in utilities' stock returns, and that this effect is statistically significant.

In Panel B, we examine the effect of changes in the *distribution* of temperature by considering a deviation of daily temperature variability from its historical mean in a given month. As will become clear later, isolating the effect of changes in temperature distribution is decisive for understanding the temperature–stock relationship, and for qualifying some of the findings in previous studies that explicitly consider temperature extremes. Crucially, and in contrast to our estimates for the deviations in (average) temperature, we find that deviations in temperature variability significantly affect energy (oil, gas and consumable fuels;

energy equipment), utilities, consumer staples (beverages, food products and tobacco; food and staples retailing; household and personal products) and consumer discretionary services (leisure products; textiles, apparel and luxury goods; hotels and restaurants; beverages; automobiles; and specialty retail).

Several channels may be at work to explain the negative impact of deviations in temperature variability on temperature-sensitive industries (Graff Zivin and Neidell (2014), Addoum et al. (2020), Addoum et al. (2021)).[16] Our findings are consistent with the consumer demand and labor productivity channels (Starr (2000); Graff Zivin and Neidell (2014)). Recall that $TD\text{-}VAR$ offers a general characterization of the unconditional probability of temperature extremes and, crucially, allows us to (i) simultaneously treat cold snaps and heatwaves as equally detrimental to economic activity, and (ii) capture day-to-day temperature swings between hot and cold. Using this measure, then, we find that many consumer-related sectors, including energy, are affected by changes in temperature variability. For example, large temperature swings can make shopping more or less difficult. Cold snaps and heatwaves can shift consumer demand patterns and may adversely impact what Starr (2000) calls "households' shopping productivity". Starr-McCluer provides empirical evidence consistent with these ideas using sector-level output data. This is also observable when considering macroeconomic output: Colacito et al. (2019) document that extreme heat in summer and autumn months affect U.S. GDP growth rates.

The results in Panels A and B demonstrate the relevance of the temperature variability effect over and above the temperature deviation effect. This divergence highlights the link between temperature and stock markets by documenting the actual impact of temperature variability on firms' operations. Deviation in temperature variability represents a more general depiction of temperature extremes than temperature deviation alone. Our measure is therefore a meaningful indicator of physical risk, which has material consequences for the stock price of firms.

In Table 8 we rerun the yearly stock return regression by splitting our sample into three time periods, illustrating the robustness of our findings across the following sub-periods: 2005–2009, 2010–2014, 2015–2020. We focus on a small group of sectors that display some interesting patterns: energy, consumer staples, and health care. The first two have significant exposure to $TD\text{-}VAR$ over the sample period 2005–2020, see Table 7 Panel B. Table 8 provides the estimates for $\widetilde{TD}$ and $TD\text{-}VAR$ for these three sectors. We report the results for all other control variables in the Appendix (A.1). Notably, the effect of $\widetilde{TD}$ remains insignificant in each sub-period, confirming the findings over the longer sample period in Table 7. Over time, the estimates of the effect of $TD\text{-}VAR$ on the energy sector decrease and then increase, and the estimates are virtually identical for consumer staples. There is no effect of $TD\text{-}VAR$ on the health care sector. These results confirm that exposure to temperature varies over time as the distribution of temperature and temperature variability changes over time (Lewis and King (2017), Alessandri and Mumtaz (2021)).

Given our initial sector-level evidence for the greater relevance of changes in temperature

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

variability over temperature deviations, a natural follow-up question is whether financial market participants efficiently account for information on temperature deviation $\widetilde{TD}$ and deviations in temperature variability $TD\text{-}VAR$. To answer this question, we shift our focus to markets' *reactions* to both temperature deviation $\widetilde{TD}$ and deviations in temperature variability $TD\text{-}VAR$.

5.2 Reactions to local temperature information

In the previous section we perform an asset pricing factor analysis and examine the significance of the two temperature metrics. We continue our investigation into the relationships between these temperature metrics and expected stock returns by examining investors' reactions to state-level heterogeneity in temperature metrics. Specifically, we examine whether investors could reduce their exposure to temperature by focusing on local temperature information. To hedge against temperature, investors would buy (short-sell) stocks in states characterized by higher (lower) $\widetilde{TD}$ and $TD\text{-}VAR$, thus increasing (reducing) the prices of these stocks and reducing (increasing) their return.

First, we sort states into quintiles based on their $\widetilde{TD}$ and $TD\text{-}VAR$ exposure, and sort stocks depending on companies' headquarter locations. Then, we form long–short spread portfolios: going long in the portfolio that includes states with the least exposure to $\widetilde{TD}$ and $TD\text{-}VAR$, and going short in the portfolio that includes states with the highest exposure to TD and $TD\text{-}VAR$. We examine whether the spread portfolios yield a statistically significant abnormal performance. If they do, this would suggest that investors do react to temperature information and, specifically, that they are pricing in the risk of temperature deviation, TD, and/or the risk of deviations in temperature variability, $TD\text{-}VAR$,.

Our portfolio-sorting approach allows us to capture the heterogeneity in temperature across the U.S., similarly to Barber et al. (2001) and Hong et al. (2020). The trading strategy is constructed as follows. At the end of each month t, we rank states according to the specific realization of $\overline{TD}$ and $TD\text{-}VAR$ in month t. Separately, we rank states based their $\widetilde{TD}$ and $TD\text{-}VAR$, and sort them into quintiles; we form $\widetilde{TD}$ and $TD\text{-}VAR$ quintiles separately. Each firm headquartered in a particular state is placed in one of the five quintiles for $\widetilde{TD}$ and then for $TD\text{-}VAR$. The first $\widetilde{TD}$ quintile portfolio, for example, consists of firms in those states with the lowest values for temperature deviation. We consider these firms to have the lowest exposure to temperature deviation. For each quintile, we compute the portfolio's post-ranking value-weighted monthly return. Next, we compute the long–short spread portfolio's monthly return. We repeat the process until we exhaust our sample period. This yields a time series of 167 spread portfolio monthly returns.

To fix ideas, at time t, the value-weighted return, R, of a quintile portfolio $p = \{1, 2, 3, 4, 5\}$ is:

$$R_{pt} = \sum_{i=1}^{n_{pt-1}} x_{it-1} r_{it}. \tag{14}$$

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

Table 14 reports the mean excess returns net of the U.S. risk-free rate. We also report portfolio alphas adjusted using the Fama-French three-factor model (Fama and French (1993)), which controls for the market factor as well as size and book-to-market factors; and the Fama-French-Carhart (Carhart (1997)) four-factor model, which includes Carhart's momentum factor. The middle three quintiles are grouped together by equal-weighting their respective returns.

In the first column of both panel A and B in Table 14, the mean excess returns are largest in the first quintile portfolio, decline for portfolios 2-4, and increase slightly in the 5th quintile. The mean excess return for states in the bottom quintile portfolio of $\widetilde{TD}$ and TD-VAR is 0.81% per month and 0.74% per month, respectively; for states in the top quintile, the mean excess return is 0.88% and 0.07%, respectively. The difference between quintile 1 (least exposed firms) and quintile 5 (most exposed firms) is 0.07% per month (t=x.xx) in excess returns for $\widetilde{TD}$ and 0.28% per month (t=x.xx) in excess returns for TD-VAR. This is a respectable 47% return over the 14-year sample period. In columns (2) and (3), we report the portfolio alphas adjusted using the three-factor and the four-factor models, respectively. Notably, results are statistically significant only for TD-VAR when including all four factors. These results suggest that markets hedge the risk from deviations in temperature variability TD-VAR, rather than the risk from temperature deviation $\widetilde{TD}$.

To the extent that local temperature anomalies might be concentrated in certain states, the significant return spread of our long–short portfolio could reflect compensation for exposure to a specific location or state risk. This is a plausible alternative as some states might be systematically exposed to continual increases or decreases in temperature deviation, or to deviations in temperature variability. Chronic exposure to abnormal temperatures would result in lower returns across the board for firms headquartered in these states. These firms could conceivably be less productive if the state in which they are headquartered is subjected to a barrage of temperature shocks. To explicitly control for location or state risk, we follow Barber et al. (2001), and construct two 5 X 5 transition matrices that illustrate the percent of times a state shifts to a different quintile of TD and TD-VAR, respectively, at month $t+1$. Table 9 reproduces the two 5 X 5 transition matrices. The starting quintile of the state is shown in the left-most column, while its quintiles at time $t+1$ are shown as the remaining columns. To shed more light on the influence of each temperature metric on the construction of the two portfolio strategies, we examine the frequency of states appearing in the first (least exposed) and fifth (most exposed) quintiles for both TD and $TD-VAR$ during our sample period. These figures are reported in Table 10.

The diagonal of the transition matrix in Panel B of Table 9 reveals that exposure to $TD-VAR$ is fairly persistent as some states do not move out of their initial quintile. The top left value in Panel B reports that a firm beginning in quintile 1 has a 52.29% chance of remaining in the first quintile. The values decline as we move into the middle quintiles, which suggests that exposure to $TD-VAR$ is persistent. Some states are either extremely exposed to deviations in temperature variability or not at all, and tend to stay near their quintile of exposure. Thus, exposure to $TD-VAR$ is dependent on the state. In contrast, exposure to temperature deviations (Panel A) is more erratic and less state-dependent. Fewer states are consistently exposed to extreme temperature deviations. For example, states in the fifth quintile are less likely to stay in this quintile, as the largest value in Panel A of Table 9 is 25.36% compared to its $TD - VAR$ counterpart of 55.54%. Results reported in Panel A of Table 9 therefore suggest that exposure to temperature deviation is less concentrated, or, equivalently, that most states are equally exposed to temperature deviations. This phenomenon is further illustrated in Table 10, which shows how often a state transitions from one quintile portfolio to another. Generally, changes in states' sorting order occurs 25%–40% more frequently when the ranking is based on their $\widetilde{TD}$ rather than their TD-VAR. The persistence of states' exposure to TD-VAR tells us that large changes in temperature variability are more concentrated vis-à-vis large changes in temperature. Temperature deviations occur uniformly across the U.S., with few states systematically subjected to large deviations in temperature. In contrast, a few states are continually unaffected by deviations in temperature variability.

These results highlights a significant difference between $TD - VAR$ and $\widetilde{TD}$. The idiosyncratic persistence of $TD - VAR$, particularly in the first and fifth quintiles, could influence the construction of our portfolio strategy. In fact, the tops and bottom of our $TD - VAR$ rankings are dominated by two states each: the Dakotas are consistently in the least exposed portfolio, Panel A in Table 11 for over half the sample period; Alaska and California are consistently in the most exposed portfolio, Panel B in Table 11. Crucially, these four states are continually exposed to low and high values, respectively, for deviations in temperature variability. State rankings in the middle quintiles tend to vary more frequently across quintiles and are less bound to their original exposure. Table 12 displays the TD equivalent. One peculiarity is that North Dakota, Montana, Idaho, Kansas, Nevada and Wyoming occur in both the first and fifth quantiles of $\widetilde{TD}$. Crucially, this indicates large swings in temperature deviations in these states; this is aptly captured by our TD-VAR measure, with some of these states appearing in the most exposed quintile in Panel B of Table 11. An issue with the infrequent rebalancing of states such as Alaska, California and the Dakotas is that the results of the portfolio strategy may be dominated by the firms in these states. This clustering in the first and last quintiles may drive the results and invalidate sorting based on temperature. To check the robustness of our results, we therefore focus our attention on TD-VAR and perform the same portfolio strategy a second time, excluding Alaska, California, North Dakota and South Dakota. We believe that the removal of these four states is sufficient because the frequency of the remaining states in the first and fifth quintiles is comparable to their counterparts in 12. Results are reported in Table 13. When we calculate the total market-adjusted return over the 14-year sample period, the strategy produces a 66% net return – an increase of 16% compared to the previous long–short strategy. This result is driven by the smaller negative coefficient of -0.1094 in the fifth quintile. In contrast, the returns to portfolios sorted on temperature deviations $\widetilde{TD}$ are insignificant.[17]

To further explore investors' reactions to state-level heterogeneity in temperature metrics, we examine whether long–short portfolio strategies that only consider the temperature-sensitive sectors identified in the previous section exhibit monthly returns that differ from the all-industries average. We form long–short spread portfolios considering energy, utilities, consumer staples and consumer discretionary sectors (Panel A in Table 15). We then remove the utilities sector (Panel B) since electric and gas utilities tend to operate in the same state

[17]Results are not tabulated but are available from the authors upon request.

in which they are headquartered. For utilities, operational processes and consumer demand effects are relevant location-specific risks. By the same token, we remove the energy sector (Panel C). Furthermore, there are 57 energy companies headquartered in Texas, constituting approximately 45% of the energy sector. These companies are excluded from the analysis in order to reduce potential bias in those strategies where Texas appears in the first or last quintile. Panel A in Table 15 reports monthly returns of the long–short spread portfolios considering all four temperature-sensitive sectors. The strategy earns a remarkable 0.389% per month in excess returns adjusted for TD-VAR, and a negative 0.65% per month in excess returns adjusted for $\widetilde{TD}$ (Panel A2 in Table 16). We are, however, modest about our excess predictability results since our portfolios are poorly diversified across industries.

The returns from the long–short strategy increase substantially when removing the utilities sector, Panel B in Table 15. The monthly excess adjusted return moves to 0.869% (t=x.xx) for TD-VAR and -0.065% for $\widetilde{TD}$ in Panel B2 of Table 16). When removing both energy and utilities, the long–short strategy for $TD - VAR$ generates an unremarkable adjusted excess return of 0.286% (t=x.xx) for TD-VAR, compared to the equivalent $\widetilde{TD}$ portfolio of 0.054% (t=x.xx). Collectively, the large differential in the monthly gross excess returns between $\widetilde{TD}$ and TD-VAR present strong evidence that investors hedge deviations in temperature variability rather than deviations in temperature. These results underscore a considerably larger reaction to deviations in temperature variability than deviations in temperature. Moreover, combined with the findings in Section 5.1, our results support the hypothesis that operating costs are a significant driver of state-specific temperature effects among energy and utilities sectors. For the consumer sectors, our results suggest that location-specific variability in temperature deviations has a lesser effect. The profitability effects among these industries tend to be driven by revenues rather than operating costs (Addoum et al. (2020)). Furthermore, the firms in these sectors have numerous brick-and-mortar stores spread across the U.S., which our aggregation method may fail to fully capture.

Overall, the results from our asset pricing tests show that TD-VAR is a significant factor for firm stock prices when the shock occurs at a firm's headquarters, especially for the utilities and energy sectors. We expect our methodology to *underestimate* the true stock price reaction from temperature shocks due to data limitations. Using granular data on exact firm operations spatially overlaid with TD-VAR would likely lead to even larger coefficients in our cross-sectional analysis, and greater adjusted returns using our trading strategy.

6 Identifying channels of price reaction

Our prior analysis strongly suggests that exposure to $TD\text{-}VAR$ has serious implications for firm stock prices and investors; however, we are agnostic as to the exact mechanism that dictates the price. Theoretically, there are two vectors at play. The first channel is investors' beliefs about companies that are exposed to temperature volatility. Heightened temperature variability acts as a "wake-up call" for investors, drawing attention to the risks of climate change, changing demand and simultaneously moving the equilibrium stock price of the exposed firm. The second, more direct channel, is the tangible, physical realization of the temperature shock on the firm's financial performance (Pankratz and Schiller (2021)).[18] The shock may lead to declines in revenues and profits, which are incorporated into the stock price.

6.1 U.S. country– and state-level attention

To test the first channel, we estimate the relationship between innovations in attention news indices and $TD\text{-}VAR$ and $\widetilde{TD}$. Innovations in attention are crucial, as expected news regarding climate change should not move the equilibrium prices of assets.[19] Investors should only react abnormally to unexpected news, thus we use the residuals from an autoregressive model with lag one for both country– and state-level indices. Investors should react to unexpected temperature swings by selling the exposed firm accordingly.

To test the relationship between unexpected changes in climate change attention and temperature volatility, we regress innovations indices on $TD\text{-}VAR$ and $\widetilde{TD}$ along with various fixed effects:

$$\epsilon_{AttentionIndex,s,t} = \alpha + \beta_T * TD\text{-}VAR_{s,t} + \beta_D * \widetilde{TD}_{s,t} + \rho_t + \gamma_s + \epsilon_{s,t}. \tag{15}$$

where the dependent variable is the AR(1) innovations in a particular country or state, s, index, ρ_t represents the time fixed effect and γ_s is the state fixed effects, when needed.

Aggregate attention is known to be a driver of asset prices. We adopt the innovations of the WSJ climate news index as our aggregate climate attention measure, as developed by Engle et al. (2020). Their research has sparked a growing literature on climate attention and the subsequent pricing of climate risks due to heightened attention. Engle et al. (2020) build the index from WSJ news articles that contain a discussion on climate change. Specifically, their measure captures the intersection between the news article text on climate change and the primary governmental or research source on which the article is based. Their assertion is that news articles on climate change are published more frequently when there climate concerns are apparent. Their narrative index connects an increase in news coverage of climate change with a heightened awareness of climate risks among investors. Direct investor attention toward a company, however, is difficult to capture and empiricists chiefly use indirect proxies (Da et al. (2011)). The WSJ index is an example of such an indirect proxy.

[18] For a deeper discussion on the exact channels of exposure, see Section 5.

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

The results of the U.S. country-level regressions are found in Table 17. Here, we find evidence of investor reaction to $TD - VAR$ rather than to $\widetilde{TD}$. The coefficients of TD-VAR in columns 1 and 3 are significant at the 10% level. When TD-VAR increases by one standard deviation, there is an associated increase in $\epsilon_{AttentionIndex,s,t}$ by (0.2482 x 0.00140 =) 0.00035 or 58% of the mean of the innovations index. Adding both year and month fixed effects, however, cuts the coefficient by half, likely due to the variation captured by additional fixed effects. The coefficients on TD are non-significant and therefore indistinguishable from zero. The results indicate that TD-VAR has a moderate relationship with the publication of climate-related news across the U.S. This association suggests that considerable unexpected temperature swings act as "wake-up calls" and grab the attention of news agencies and, subsequently, investors across the nation. The weaker relationship between TD-VAR and the WSJ index is likely due to the spatial aspect of the shock. Realistically, shocks to TD-VAR do not occur simultaneously throughout the U.S. but are instead highly localized. These attention-grabbing events will theoretically have a more substantial impact at the state level, which is represented in our state-level analysis.

Our results suggest that the number of unplanned articles written about climate change are positively and contemporaneously correlated with TD-VAR. However, we are agnostic as to the type of investor, as well as to whether investors do in fact read the articles that are published, as attention is a scarce resource. Nevertheless, the results thus far imply that investors are affected by elevated news coverage of climate risks, which lead to the pricing effects in Section 5.

Continuing our investigation of the first channel, we expect that less granular measures of investor attention, such as Engle et al. (2020), may not capture the rich geographic heterogeneity of TD-VAR and $\widetilde{TD}$, as climate shocks are inherently regional (Alekseev et al. (2021)). Choi et al. (2020), for example, find that deviations in temperature only shift investor attention when they are substantial. To better capture the spatio-temporal distribution of temperature volatility, we associate temperature volatility shocks with local attention indices. We gather state-level Google SVI data on "Climate Change" and "Temperature", which should encompass reactions from retail investors and, to a lesser extent, from institutional investors (Da et al. (2011)). Specifically, we regress unexpected state-level SVI for each topic on the temperature volatility measures; the result is shown in Table 18.

The results of the state-level regressions show a positive and strongly significant relationship between TD-VAR and index innovations. The coefficients for TD-VAR are always significant at the 1% level and hover around 0.76 for both risk topics. TD is insignificant in the first panel, suggesting that deviations in temperature alone do not raise attention. The TD coefficient, however, becomes highly significant in the second panel which is likely due to the higher relevance of the temperature topic to TD. A one standard deviation increase in TD-VAR and $\widetilde{TD}$ leads to an increase in innovations by 35 and 25, respectively. The larger effect size of TD-VAR substantiates our claim that this is the more salient metric. The results largely support our rationale that high intensity deviations from expected weather events affect investor attention.

We present U.S. country– and state-level evidence that temperature variability shocks, indicated by TD-VAR, are linked to investor attention. Our results are consistent with the interpretation that elevated TD-VAR should "wake up" local investors and prompt an interest in climate risks, which then leads to a greater volume of searches in an exposed state. In comparison to the WSJ index, SVI is a revealed measure of attention as it implies that investors are directly paying attention to the topic (Da et al. (2011). The strong significance of the coefficients also strengthens the argument that attention is spatially dependent. In aggregate, the attention results show that *TD-VAR* is a driver of unexpected attention toward climate change. This attention channel is one explanation of why investors reallocate their portfolios.

6.2 Firm-level impact beyond attention

We investigate the second vector by distilling the realized impact of temperature shocks from firm-level earnings gleaned from conference call transcripts. We adopt a physical climate exposure measure by Sautner et al. (2020) who use these earnings call transcripts to develop a time-varying measure of firm-level exposure to physical climate change risks.[20] Earnings calls can be considered a more reliable gauge of climate exposure than management statements, such as annual reports, because the discourse includes both management and analysts. We argue that there is considerable overlap between attention and climate discourse as both investors and management may raise the issue during periods of global attentiveness. The results of Sautner et al. (2020) confirm this view, finding a positive relationship between the WSJ index developed by Engle et al. (2020) and their physical climate measure. To disentangle the material impact of the temperature shock from the effects of attention, we obtain residuals from a regression of expected and unexpected attention on physical climate exposure created by Sautner et al. (2020).[21] Formally, we define this as:

$$PhysCCExposure_{i,t} = \alpha + \beta_1 * AttentionIndex_t + \beta_2 * \epsilon_{AttentionIndex,t} + \gamma_i + \epsilon_{NetExposure,i,t}. \quad (16)$$

Here we obtain $\epsilon_{NetExposure,i,t}$ as the remaining residual, which we argue contains the concrete impact of physical climate change exposure $PhysCCExposure$, beyond attention, for firm i at time t. We then regress our temperature shocks on this residual value to identify whether the shock had a tangible impact on firm-level operations. We formally define this by including the s subscript, which represents the state in which the firm is headquartered:

$$\epsilon_{NetExposure,i,t} = \alpha + \beta_T * TD\text{-}VAR_{s,t} + \beta_D * \widetilde{TD}_{s,t} + \gamma_i + \epsilon_{i,s,t}. \quad (17)$$

The main variation occurs at the state-quarter level, as this is where firms are exposed to time-varying temperature shocks. Our assumption here, similar to Section 5.2, is that the operational footprint of the firm is located in the headquartered state. While some literature, such as Pankratz and Schiller (2021) and Addoum et al. (2020), has granular data on firm establishments, we believe this generalization is still useful in capturing the spatial effects of the shock.

[20] We limit ourselves to physical climate exposure because temperature shocks are a realized form of a physical climate shock.

[21] We only use the WSJ news index as it is the only attention measure used in Sautner et al. (2020). We adapt the WSJ index by taking the average over a quarter and finding the series' AR(1) residuals.

The results of Equation 17 with various sector samples are shown in Table 19. The first column of the table shows a positive, significant association with $TD\text{-}VAR$ and NetExposure for all firms in this sample. We interpret these results as $TD\text{-}VAR$ being associated with an increase in the proportion of an earnings call that discusses physical climate change exposure. Here, the conversation is not associated with broad climate attention, but rather with the *realized* physical exposure of the firm. When we exclude the utilities and energy sectors in column 2, the coefficient decreases slightly but retains its significance. The third column, which includes both the utilities and energy sectors, also displays a large positive coefficient between $TD\text{-}VAR$ and NetExposure. The utilities and energy sectors' high degree of sensitivity to $TD\text{-}VAR$ is consistent with prior evidence Section 5. In column 4, there is a positive, insignificant relationship between temperature shocks for the consumer discretionary and consumer staples sectors. The results are coherent with our Section 5 results, which suggested that the state-headquarter level inadequately represents the physical risk profile of consumer sector firms.

7 Conclusion

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

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

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

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8 Tables

Table 1: Specification of city dataset

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

Table(1). Present the characteristics of the city for which we obtain GHNC daily data from NOAA. The stations coincide with the city airport where is not clear. The columns weather derivatives indicates the stations for which a Cooling Degree Days (CDD) or Heating Degrees Day (HDD) weather derivative is traded at CME.

Table 2: Summary Statistics, Russel 3000

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

Table(2). The table presents summary statistics for the control variables of the Russell 3000 index component. We print the average of each indicator by equi-weighting the single components each year. LOGSIZE is the natural logarithm of the market capitalization; B/M is firm's book value divided by its yearly market cap; ROE is the ratio of firm's net yearly income divided by the value of its equity; LEVERAGE is the ratio of debt to book value of assets; capital expenditures INVEST/A, is the firm's yearly capital expenditures divided by the book value of its assets; LOGPPE, is the natural logarithm of the firm's property, plant, and equipment; MOM is the average of returns on stock, for the 12 months' up to and including month t 1

Table 3: Summary Statistics, Fama French 3 Factors

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Mkt-RF	0.28	0.83	0.12	-3.68	2.28	1.49	0.14	1.31	2.57	0.96	0.08	1.09	1.63	-0.49	2.13	2.07	2.69
SMB	-0.02	0.18	-0.64	0.53	0.67	1.02	-0.37	0.01	0.48	-0.56	-0.48	0.73	-0.41	-0.39	-0.36	0.51	1.84
HML	0.73	0.86	-1.41	0.17	-0.23	-0.30	-0.70	0.71	0.18	-0.13	-0.84	1.62	-0.96	-0.87	-0.68	-2.92	4.15
RF	0.25	0.39	0.38	0.13	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.02	0.07	0.15	0.18	0.04	0.00

Table(3). The table shows the yearly average for the three Fama-French factors. Source: Kenneth French repository (French (2020)). From the top to the bottom, the first, Market minus Risk Free(Mkt-RF). is the market excess return over the risk free. Small Minus Big (SMB) is the return of the least capitalized over the most capitalized. High minus low (HML) represent the spread between value and growth stocks. Risk Free (RF) is the U.S. risk free rate.

Table 4: Pearson Correlation Coefficient, Temperature drivers

	T	TD	$\sigma(TD)$	$TD\text{-}VAR$
T	1			
TD	0.32	1		
$\sigma(TD)$	-0.8	-0.11	1	
$TD\text{-}VAR$	-0.2	-0.12	0.17	1

Table (4). Sample period: 2005-2020. It is computed the Pearson correlation coefficient on the level of the variables. The entries represent Temperature level, temperature deviation (TD, 1), temperature variability (3), deviation in temperature variability (TDVAR, 4).

Table 5: Estimation of Weather Derivates price driver

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

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

Table (5). Sample period is 2015-2020. Estimation of model 12 for different specification. The dependent variabile is CDD and HDD respectively and the main independent variable is T_m that represent the maximum temperature minus 65°F, threshold level for futures contract traded at CME. Model (1) considers only T_m as regressor, that represent the underlying. (2) considers all the regresses.Estimation is run trough a PanelOLS employing fixed effect for entities and time. Standard errors are clustered both at entity and time levels

Table 6: Estimation Results for energy consumption

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

Standard errors reported in parentheses

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

Table (6) The sample period is 2005-2020. The Table present the estimated coefficient for equation $\epsilon_t = \beta_v * TDVAR + \beta_t * TD + \gamma_t + \eta_n + \epsilon$ in the different sectors, Residential, Commercial, Industrial and the aggregated. Estimation is run trough a PanelOLS employing fixed effect for entities and time. Standard errors are clustered both at entity and time levels. The sample period is 2005-2020 for the 50 US state. $\widetilde{TD}$ and $TD\text{-}VAR$ are the state level temperature measure as defined in equation (19, 18)

Table 7: Estimation for TD(A) and $TD\text{-}VAR$(B) on stock return

Panel A: Deviation of temperature

Dep. Variable: r	All	Ind	Energy	Health	IT	Utilities	Staple	C. Disc	Mat	Fin	Comm
$\widetilde{TD}$	0.0197	0.0510	0.1452	0.0852	-0.0076	-0.1004**	-0.0036	-0.0268	-0.0780	0.0119	-0.0101
	(0.9529)	(1.1508)	(0.9032)	(0.8592)	(-0.1381)	(-2.5604)	(-0.0500)	(-0.5041)	(-1.0290)	(0.3195)	(-0.1021)
LOGSIZE	-4.0221***	-4.3981***	-2.7935***	-4.0251***	-4.5562***	-3.1566***	-4.6041***	-5.1566***	-5.7560***	-2.8803***	-4.4655***
	(-27.758)	(-11.816)	(-5.6288)	(-8.2804)	(-9.5827)	(-7.0067)	(-8.3714)	(-14.519)	(-12.504)	(-11.977)	(-7.3882)
B/M	0.0028	0.0042	-0.0456*	-0.0224	0.0447*	0.0349	0.0355	0.0269	0.1293***	-0.0177*	0.0552**
	(0.4185)	(0.2098)	(-1.9141)	(-1.1148)	(1.7702)	(1.5437)	(1.5955)	(1.1453)	(4.6954)	(-1.7409)	(2.0166)
ROE	0.0421***	0.0360***	0.0181	0.0351***	0.0517***	0.0619***	0.0486***	0.0516***	0.0706***	0.0795***	0.0345***
	(12.679)	(4.1566)	(1.1995)	(4.4550)	(6.9696)	(2.8095)	(3.2003)	(8.2675)	(6.9395)	(6.4879)	(3.5929)
LEVERAGE	-6.228e-05	0.0014	-0.0255	-0.0001	0.0361***	-0.0033	0.0180	-0.0420***	0.0152	-0.0213**	0.0223
	(-0.1042)	(0.1429)	(-1.2480)	(-0.2092)	(2.6880)	(-0.1727)	(1.2436)	(-2.8260)	(0.9949)	(-2.2622)	(1.0244)
INVEST/A	0.0563**	0.0501*	0.0913	0.0618	0.0439	0.0126	0.1058*	-0.0246	0.0025	-0.1464*	-0.0403
	(1.9619)	(1.6797)	(1.5282)	(1.1325)	(0.6122)	(0.3603)	(1.9201)	(-0.8990)	(0.0481)	(-1.8887)	(-0.6033)
LOGPPE	0.3849***	0.9937***	1.7880*	-0.3065	-0.0303	0.1252**	0.9673***	0.8023***	0.7069*	0.4224**	0.9395**
	(3.7273)	(3.7276)	(1.8732)	(-0.8975)	(-0.0955)	(2.3325)	(3.7254)	(2.6222)	(1.7622)	(2.2345)	(2.4444)
MOM	-0.0431**	0.0235	-0.1375	-0.0134	-0.0499	-0.0545	0.0437	-0.0692*	0.0504	-0.2512***	-0.1031
	(-2.3345)	(0.5090)	(-1.2486)	(-0.2569)	(-1.1200)	(-0.5840)	(0.6600)	(-1.6582)	(0.8254)	(-5.3834)	(-1.2196)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	141827	26670	6731	17509	18058	6321	7441	18543	8911	22365	5380
Cov. Est.	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R-squared	0.0220	0.0237	0.0239	0.0138	0.0294	0.0210	0.0278	0.0355	0.0406	0.0279	0.0314

Panel B: Deviation of temperature variability

Dep. Variable: r	All	Ind	Energy	Health	IT	Utilities	Staple	C. Disc	Mat	Fin	Comm
TD-VAR	-0.0984	-0.2476	-0.9477**	0.4770	0.2354	0.3552**	-0.9432***	-0.6084***	0.0163	-0.0670	0.5953
	(0.0759)	(0.1541)	(0.4652)	(0.3478)	(0.2283)	(0.1538)	(0.2646)	(0.2236)	(0.2770)	(0.1357)	(0.4177)
LOGSIZE	-4.0223***	-4.3964***	-2.7972***	-4.0210***	-4.5571***	-3.1496***	-4.6158***	-5.1595***	-5.7561***	-2.8808***	-4.4402***
	(0.1449)	(0.3723)	(0.4961)	(0.4868)	(0.4755)	(0.4501)	(0.5489)	(0.3551)	(0.4605)	(0.2404)	(0.6057)
B/M	0.0029	0.0042	-0.0459*	-0.0232	0.0451*	0.0360	0.0353	0.0278	0.1289***	-0.0177*	0.0536*
	(0.0067)	(0.0200)	(0.0238)	(0.0201)	(0.0253)	(0.0226)	(0.0222)	(0.0235)	(0.0275)	(0.0102)	(0.0275)
ROE	0.0421***	0.0359***	0.0179	0.0350***	0.0518***	0.0616***	0.0486***	0.0516***	0.0705***	0.0794***	0.0347***
	(0.0033)	(0.0087)	(0.0150)	(0.0079)	(0.0074)	(0.0220)	(0.0152)	(0.0062)	(0.0102)	(0.0123)	(0.0096)
LEVERAGE	-6.133e-05	0.0012	-0.0261	-0.0001	0.0362***	-0.0043	0.0179	-0.0417***	0.0148	-0.0213**	0.0221
	(0.0006)	(0.0097)	(0.0204)	(0.0006)	(0.0134)	(0.0189)	(0.0145)	(0.0149)	(0.0153)	(0.0094)	(0.0218)
INVEST/A	0.0564**	0.0502*	0.0922	0.0575	0.0441	0.0134	0.1048*	-0.0245	0.0032	-0.1464*	-0.0430
	(0.0287)	(0.0298)	(0.0596)	(0.0547)	(0.0717)	(0.0351)	(0.0550)	(0.0273)	(0.0515)	(0.0776)	(0.0668)
LOGPPE	0.3850***	0.9949***	1.8210*	-0.3006	-0.0319	0.1170**	0.9734***	0.7981***	0.7175*	0.4214**	0.9523**
	(0.1033)	(0.2666)	(0.9533)	(0.3400)	(0.3172)	(0.0536)	(0.2603)	(0.3062)	(0.4015)	(0.1890)	(0.3845)
MOM	-0.0430**	0.0237	-0.1369	-0.0135	-0.0502	-0.0561	0.0468	-0.0698*	0.0516	-0.2513***	-0.1056
	(0.0185)	(0.0460)	(0.1104)	(0.0521)	(0.0446)	(0.0932)	(0.0662)	(0.0417)	(0.0611)	(0.0467)	(0.0843)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	141827	26670	6731	17509	18058	6321	7441	18543	8911	22365	5380
Cov. Est.	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R-squared	0.0220	0.0237	0.0243	0.0139	0.0295	0.0209	0.0295	0.0359	0.0405	0.0279	0.0317

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

Table (7). The sample period is 2005-2020. All variables are defined in Tables (2) in the Data section. The independent variables include the deviation of daily temperature from its historical mean within a month (Panel A) or the deviation of daily temperature variability from its historical mean in the a month (Panel B). We use the Global Industry Classification Standard to identify a firm's sectoral affiliation. We consider the following sectors: Information Technology (IT), Health Care (Health), Financials (Fin), Consumer Discretionary (C. Disc), Communication Services (Comm), Industrials (Ind), Consumer Staples (Staple), Energy, Utilities, Real Estate (RE), and Materials (Mat). We refer to this document for an overview of the classification: `http://www.msci.com/our-solutions/indexes/gics`. We report the results of the panel regression with standard errors clustered at the firm and year levels. All regressions include month fixed effects and firm fixed effects.

Table 8: Estimation for $\widetilde{TD}$ and $TD\text{-}VAR$, three sector, different periods

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

Standard errors reported in parentheses

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

Table(8). The sample period 2005-2020 is divided into three equal sub-periods. The independent variables include in turn the deviation of daily temperature from its historical mean within a month (first row) or the deviation of daily temperature variability from its historical mean in the a month (second row). We report the results of the panel regression with standard errors clustered at the firm and year levels. All regressions include month fixed effects and firm fixed effects

Table 9: Quintile Transition Matrices: TD (A) TD-VAR (B)

Panel A

	Rebalanced Quintile 1	2	3	4	5
Quintile 1	22.47	22.23	17.95	17.53	19.82
Quintile 2	20.48	20.78	21.08	19.34	18.31
Quintile 3	18.49	19.82	22.29	21.39	18.01
Quintile 4	19.52	20.36	20.72	20.90	18.49
Quintile 5	19.04	16.81	17.95	20.84	25.36
Total	100	100	100	100	100

Panel B

	Rebalanced Quintile 1	2	3	4	5
Quintile 1	52.29	24.82	14.10	5.54	3.25
Quintile 2	24.40	31.39	22.77	14.88	6.57
Quintile 3	12.41	24.28	28.98	22.95	11.39
Quintile 4	7.65	13.61	23.67	31.81	23.25
Quintile 5	3.25	5.90	10.48	24.82	55.54
Total	100	100	100	100	100

Table(9). The sample period is 2006–2020. This table illustrates the frequency of states moving to another quintile of exposure. Panel A represents the transition matrix of the portfolio strategy when using $\widetilde{TD}$ and Panel B represents $TD\text{-}VAR$. The left-most column of each panel is the beginning exposure quintile of the state. The other columns represents the exposure quintile of the state in the next month. Each number represents the percent of times a state moves from one quintile to another.

Table 10: Frequency of Rebalancing: TD (A) TD-VAR (B)

Panel A

Country	Transitions	Rank
MAINE	142	1
DELAWARE	139	2
PENNSYLVANIA	138	3
OHIO	138	4
MISSISSIPPI	137	5
WISCONSIN	137	6
NEWHAMPSHIRE	137	7
ILLINOIS	136	8
NEWYORK	136	9
CALIFORNIA	135	10
	⋮	⋮
KANSAS	123	40
TENNESSEE	122	41
LOUISIANA	122	42
CONNECTICUT	121	43
TEXAS	121	44
NORTHDAKOTA	121	45
FLORIDA	121	46
SOUTHCAROLINA	119	47
WASHINGTON	118	48
WYOMING	118	49
IDAHO	115	50

Panel B

Country	Transitions	Rank
FLORIDA	113	1
VIRGINIA	112	2
KENTUCKY	112	3
WISCONSIN	111	4
LOUISIANA	111	5
TENNESSEE	109	6
COLORADO	109	7
INDIANA	107	8
OHIO	107	9
NORTHCAROLINA	106	10
	⋮	⋮
ARKANSAS	94	40
IDAHO	94	41
MISSISSIPPI	92	42
OKLAHOMA	92	43
CALIFORNIA	91	44
KANSAS	91	45
MONTANA	87	46
OREGON	85	47
NORTHDAKOTA	82	48
SOUTHDAKOTA	80	49
ALASKA	79	50

Table (10). The sample period is 2006–2020. These tables show the frequency of states transitioning from one quintile to another for the portfolio strategy using $\widetilde{TD}$ (Panel A) or $TD - VAR$ (Panel B). The first ten rows of the table show states that are often being rebalanced from one quintile to another while the second ten show states that remain in a quintile. The transition corresponds to the number of times a state rebalanced. The rank column denotes ranking of the number of times a state is rebalanced among the 50 states.

Table 11: Frequency of State in Quintile TD-VAR: 1st (A) 5th (B)

Panel A

	Freq.	Percent	Cum.
NORTHDAKOTA	94	5.63	5.63
SOUTHDAKOTA	94	5.63	11.26
MONTANA	65	3.89	15.15
NEBRASKA	57	3.41	18.56
OKLAHOMA	52	3.11	21.68
MAINE	51	3.05	24.73
WASHINGTON	50	2.99	27.72
MINNESOTA	48	2.87	30.60
IOWA	47	2.81	33.41
ALABAMA	46	2.75	36.17
	⋮	⋮	⋮
RHODEISLAND	20	1.20	91.98
ARIZONA	19	1.14	93.11
CALIFORNIA	19	1.14	94.25
PENNSYLVANIA	19	1.14	95.39
NEWJERSEY	17	1.02	96.41
UTAH	16	0.96	97.37
VIRGINIA	16	0.96	98.32
ALASKA	10	0.60	98.92
WESTVIRGINIA	10	0.60	99.52
KENTUCKY	8	0.48	100.00
Total	1670	100.00	

Panel B

	Freq.	Percent	Cum.
ALASKA	94	5.63	5.63
CALIFORNIA	74	4.43	10.06
OREGON	64	3.83	13.89
KANSAS	62	3.71	17.60
IDAHO	61	3.65	21.26
NEVADA	61	3.65	24.91
UTAH	56	3.35	28.26
MICHIGAN	50	2.99	31.26
TEXAS	49	2.93	34.19
ARIZONA	48	2.87	37.07
	⋮	⋮	⋮
FLORIDA	19	1.14	92.63
OHIO	18	1.08	93.71
NORTHDAKOTA	16	0.96	94.67
VIRGINIA	16	0.96	95.63
ALABAMA	15	0.90	96.53
MAINE	15	0.90	97.43
GEORGIA	12	0.72	98.14
SOUTHCAROLINA	12	0.72	98.86
HAWAII	11	0.66	99.52
MARYLAND	8	0.48	100.00
Total	1670	100.00	

Table (11). The sample period is 2006–2020. These tables show the frequency of states staying in a certain quintile. Panel A represents the 1st quintile when applying the portfolio strategy using $TD\text{-}VAR$ and Panel B denotes the same strategy using the 5th quintile. The first ten rows of each panel are the states that most consistently stay in either the 1st (A) or 5th quintile (B). The second ten rows of each panel are the states that least appear in either the 1st (A) or 5th quintile (B) portfolios. The frequency columns correspond to the number of times a state is found in a quintile portfolio. The percent column denotes percent of times the state is in the quintile portfolio out of all other states.

Table 12: Frequency of State in Quintile TD: 1st (A) 5th (B)

Panel A

	Freq.	Percent	Cum.
IDAHO	58	3.47	3.47
MONTANA	56	3.35	6.83
WASHINGTON	54	3.23	10.06
NORTHDAKOTA	53	3.17	13.23
NEBRASKA	51	3.05	16.29
OREGON	50	2.99	19.28
SOUTHDAKOTA	50	2.99	22.28
NEVADA	48	2.87	25.15
WYOMING	48	2.87	28.02
KANSAS	46	2.75	30.78
	⋮	⋮	⋮
TENNESSEE	22	1.32	90.66
NEWJERSEY	21	1.26	91.92
DELAWARE	20	1.20	93.11
GEORGIA	19	1.14	94.25
CONNECTICUT	18	1.08	95.33
MARYLAND	18	1.08	96.41
LOUISIANA	17	1.02	97.43
RHODEISLAND	16	0.96	98.38
MISSISSIPPI	15	0.90	99.28
ALABAMA	12	0.72	100.00
Total	1670	100.00	

Panel B

	Freq.	Percent	Cum.
KANSAS	52	3.11	3.11
MONTANA	50	2.99	6.11
NORTHDAKOTA	49	2.93	9.04
NEVADA	48	2.87	11.92
IDAHO	47	2.81	14.73
OREGON	47	2.81	17.54
WYOMING	47	2.81	20.36
OKLAHOMA	46	2.75	23.11
CALIFORNIA	45	2.69	25.81
NEBRASKA	45	2.69	28.50
	⋮	⋮	⋮
NORTHCAROLINA	23	1.38	90.12
RHODEISLAND	21	1.26	91.38
VIRGINIA	21	1.26	92.63
PENNSYLVANIA	20	1.20	93.83
DELAWARE	18	1.08	94.91
HAWAII	18	1.08	95.99
LOUISIANA	18	1.08	97.07
MARYLAND	18	1.08	98.14
CONNECTICUT	17	1.02	99.16
NEWJERSEY	14	0.84	100.00
Total	1670	100.00	

Table (12). The sample period is 2006–2020. These tables show the frequency of states staying in a certain quintile. Panel A represents the 1st quintile when applying the portfolio strategy using $\widetilde{TD}$ and Panel B denotes the same strategy using the 5th quintile. The first ten rows of each panel are the states that most consistently stay in either the 1st (A) or 5th quintile (B). The second ten rows of each panel are the states that least appear in either the 1st (A) or 5th quintile (B) portfolios. The frequency columns correspond to the number of times a state is found in a quintile portfolio. The percent column denotes percent of times the state is in the quintile portfolio out of all other states.

Table 13: Returns to Portfolios Sorted on $TD\text{-}VAR$ excluding four states

	Excess Return	**3-factor**	**4-factor**
Quintile 1	0.992***	0.275**	0.282**
	(2.913)	(2.275)	(2.379)
Quintiles 2–4	0.656**	0.001	0.001
	(2.117)	(0.023)	(0.013)
Quintile 5	0.56	-0.195	-0.190
	(1.545)	(-1.409)	(-1.382)
(1-5)	0.432	0.4703	0.395
	(x.xx)	(x.xx)	(x.xx)

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

Table (13). The sample period is from 2006 to 2020 These tables report the alpha (in percentage) to quintile portfolios sorted on $TD\text{-}VAR$. At the end of each month t, we sort states – excluding Alaska, California, North Dakota, and South Dakota – into quintile portfolios based on their $TD\text{-}VAR$, separately, using data up to month t. Returns for each quintile portfolio is the value-weighted returns of the firms headquartered in each state. Quintile 1 are those U.S. states with the lowest values of temperature variability $TD\text{-}VAR$. Quintile 5 are those countries with the highest values of temperature variability $TD\text{-}VAR$. We group the middle three quintile portfolios together by equal-weighting their respective returns and denote it as "Quintiles 2–4". We report the mean excess returns, alphas based on CAPM, three-factor model, and four-factor model. "(1–5)" reports the return spread between the top and bottom quintiles.

Table 14: Portfolio Returns based on sorting metrics

Panel A: Returns to Portfolios Sorted on TD

	Excess Return	**3-factor**	**4-factor**
Quintile 1	0.878**	0.168**	0.166
	(2.585)	(1.670)	(-1.65)
Quintiles 2–4	0.697	-0.004	-0.003
	(2.182)	(-0.061)	(-0.052)
Quintile 5	0.813**	0.115	0.117
	(2.404)	(1.023)	(-0.001)
(1–5)	0.065	0.053	0.049
	(x.xx)	(x.xx)	(x.xx)

Panel B: Returns to Portfolios Sorted on $TD\text{-}VAR$

	Excess Return	**3-factor**	**4-factor**
Quintile 1	1.014***	0.293**	0.299**
	(3.001)	(2.467)	(-2.55)
Quintiles 2–4	0.6812**	0.009	0.008
	(2.191)	(0.180)	(x.xx)
Quintile 5	0.738**	-0.003	0.000
	(2.195)	(-0.652)	(-0.001)
(1–5)	0.276	0.296	0.299
	(x.xx)	(x.xx)	(x.xx)

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

Table (14). The sample period is from 2006 to 2020. It reports the alpha (in percentage) to quintile portfolios sorted on TD (Panel A) and $TD\text{-}VAR$ (Panel B). At the end of each month t, we sort states into quintile portfolios based on their TD and $TD\text{-}VAR$, separately, using data up to month t. Returns for each quintile portfolio is the value-weighted returns of the firms headquartered in each state. Quintile 1 are those U.S. states with the lowest values of temperature deviations TD (Panel A); and lowest value of deviation of temperature variability $TD\text{-}VAR$ (Panel B). Quintile 5 are those countries with the highest values of temperature deviations TD (Panel A); and lowest value of deviation of temperature variability $TD\text{-}VAR$ (Panel B). We group the middle three quintile portfolios together by equal-weighting their respective returns and denote it as “Quintiles 2–4”. We report the mean excess returns, alphas based on CAPM, three-factor model, and four-factor model. “(1–5)” reports the return spread between the top and bottom quintiles.

Table 15: Returns to Portfolio Sorted on $TD\text{-}VAR$, sector specification

Panel A: Energy, Utilities, Consumer Staples, Consumer Discretionary

	Excess Return	**3-factor**	**4-factor**
Quintile 1	1.114***	0.435***	0.439***
	(3.172)	(2.415)	(2.388)
Quintiles 2–4	0.7253***	0.162	0.16
	(2.833)	(1.473)	(1.446)
Quintile 5	0.678**	0.055	0.050
	(2.191)	(0.333)	(0.308)
(1–5)	0.436	0.38	0.389
	(x.xx)	(x.xx)	(x.xx)

Panel B: Energy, Consumer Staples, Consumer Discretionary

	Excess Return	**3-factor**	**4-factor**
Quintile 1	1.314***	0.599**	0.622**
	(3.048)	(2.234)	(2.386)
Quintiles 2–4	0.734***	0.141	0.14
	(2.657)	(1.182)	(1.166)
Quintile 5	0.649*	-0.009	-0.011
	(1.9409)	(-0.048)	(-0.063)
(1–5)	0.665	0.608	0.869
	(x.xx)	(x.xx)	(x.xx)

Panel C: Consumer Staples, Consumer Discretionary

	Excess Return	**3-factor**	**4-factor**
Quintile 1	1.083**	0.367	0.332
	(2.475)	(1.337)	(-1.456)
Quintiles 2–4	0.810***	0.229	0.227
	(2.916)	(1.646)	(1.622)
Quintile 5	0.766	0.100	0.106
	(2.104)	(0.443)	(-0.473)
(1–5)	0.317	0.267	0.286
	(x.xx)	(x.xx)	(x.xx)

t-stats reported in parentheses

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

Table (15). The sample period is from 2006 to 2020. It reports the alpha (in percentage) to quintile portfolios sorted on $TD\text{-}VAR$. At the end of each month t, we sort states into quintile portfolios based on their $TD\text{-}VAR$ using data up to month t. Returns for each quintile portfolio is the value-weighted returns of the firms headquartered in each state. We consider exclusively Energy, Utilities, Consumer Staples, Consumer Discretionary (Panel A); Energy, Consumer Staples, Consumer Discretionary (Panel B); Energy, Consumer Staples, Consumer Discretionary (Panel C). There are 57 energy companies headquartered in Texas, constituting approximately 45% of the Energy sector. These companies are excluded from the analysis. Quintile 1 are those U.S. states with the lowest values of temperature variability $TD\text{-}VAR$. Quintile 5 are those countries with the highest values of temperature variability $TD\text{-}VAR$. We group the middle three quintile portfolios together by equal-weighting their respective returns and denote it as "Quintiles 2–4". We report the mean excess returns, alphas based on CAPM, three-factor model, and four-factor model. "(1–5)" reports the return spread between the top and bottom quintiles.

Table 16: Returns to Portfolio Sorted on TD, sector specification

Panel A2: Energy, Utilities, Consumer Staples, Consumer Discretionary

	Excess Return	**3-factor**	**4-factor**
Quintile 1	0.881**	0.213	0.214
	(2.518)	(1.200)	(1.201)
Quintiles 2–4	0.755***	0.185	0.182
	(2.888)	(1.611)	(1.586)
Quintile 5	0.946**	0.293	0.298
	(2.782)	(1.569)	(1.601)
(1–5)	-0.058	-0.08	-0.084
	(x.xx)	(x.xx)	(x.xx)

Panel B2: Energy, Consumer Staples, Consumer Discretionary

	Excess Return	**3-factor**	**4-factor**
Quintile 1	0.881***	0.241	0.239
	(2.711)	(1.508)	(1.499)
Quintiles 2–4	0.775***	0.178	0.177
	(2.769)	(1.467)	(1.452)
Quintile 5	0.923***	0.301*	0.304*
	(2.882)	(1.683)	(1.700)
(1–5)	0.665	-0.059	-0.065
	(x.xx)	(x.xx)	(x.xx)

Panel C2: Consumer Staples, Consumer Discretionary

	Excess Return	**3-factor**	**4-factor**
Quintile 1	0.946***	0.281	0.282
	(2.676)	(1.376)	(1.374)
Quintiles 2–4	0.822***	0.232	0.235
	(2.901)	(1.623)	(1.641)
Quintile 5	0.886**	0.226	0.227
	(2.411)	(1.067)	(1.101)
(1–5)	0.06	0.055	0.054
	(x.xx)	(x.xx)	(x.xx)

t-stats reported in parentheses

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

Table (16). The sample period is from 2006 to 2020. It reports the alpha (in percentage) to quintile portfolios sorted on $TD\text{-}VAR$. At the end of each month t, we sort states into quintile portfolios based on their $TD\text{-}VAR$ using data up to month t. Returns for each quintile portfolio is the value-weighted returns of the firms headquartered in each state. We consider exclusively Energy, Utilities, Consumer Staples, Consumer Discretionary (Panel A); Energy, Consumer Staples, Consumer Discretionary (Panel B); Energy, Consumer Staples, Consumer Discretionary (Panel C). There are 57 energy companies headquartered in Texas, constituting approximately 45% of the Energy sector. These companies are excluded from the analysis. Quintile 1 are those U.S. states with the lowest values of temperature variability $TD\text{-}VAR$. Quintile 5 are those countries with the highest values of temperature variability $TD\text{-}VAR$. We group the middle three quintile portfolios together by equal-weighting their respective returns and denote it as “Quintiles 2–4”. We report the mean excess returns, alphas based on CAPM, three-factor model, and four-factor model. “(1–5)” reports the return spread between the top and bottom quintiles.

Table 17: Engle Index AR(1) Residuals

	1	2	3	4	5	6
$TD\text{-}VAR$	0.00140*		0.00134*	0.000568		0.000511
	(1.82)		(1.73)	(0.60)		(0.52)
$\widetilde{TD}$		-0.000154	-0.000134		-0.0000907	-0.0000801
		(-0.91)	(-0.75)		(-0.47)	(-0.40)
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	Yes	Yes	Yes
No Observation	148	148	148	148	148	148
R-squared	0.11	0.09	0.12	0.17	0.17	0.17

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

Table(17) The table shows the estimation for Equation 15 for the sample period 2005-2017. Here, the dependent variable for all columns is the innovations on the WSJ index. The estimation is conducted through panel OLS with fixed effects at the month and year level. Models (1) and (4) considers only $TD\text{-}VAR$ as the regressor, while models (2) and (5) use $\widetilde{(TD)}$. Models (3) and (4) consider both $TD\text{-}VAR$ and TD as regressors.

Table 18: State specific Google SVI AR(1) residual

	Climate Change: Panel (A)			Temperature: Panel (B)		
	1	2	3	1	2	3
$TD\text{-}VAR$	0.77***		0.76***	0.73***		0.76***
	(0.24)		(0.25)	(0.17)		(0.16)
$\widetilde{TD}$		-0.05	-0.04		0.12**	0.13***
		(0.05)	(0.05)		(0.05)	(0.05)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	8850	8850	8850	8850	8850	8850
Cov. Est	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
R-squared	0.01	0.001	0.01	0.02	0.01	0.04

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

Table (**??**). The sample period 2005-2020. Shows the estimation for Equation 15, on the sample period 2005-2020. SVI index is considered for the quotes "Climate change", Panel (A), and "Temperature", Panel(B). Estimation is run trough Panel OLS with fixed effects for entities. Standard errors clustered at the entity levels. Model (1) considers just $TD\text{-}VAR$ as regressor, model (2) employs $\widetilde{(TD)}$ and model (3) is run considering both $TD\text{-}VAR$ and TD.

Table 19: Firm-Level Exposure to Temperature Shocks

	(1) All Industires	(2) Ex Util/Energy	(3) Util/Energy	(4) Cons Disc/Staples
$TD\text{-}VAR$	0.038***	0.032**	0.102**	0.020
	(0.014)	(0.015)	(0.050)	(0.019)
$\widetilde{TD}$	-0.006*	-0.005	-0.014	-0.004
	(0.003)	(0.003)	(0.013)	(0.005)
Firm FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Observations	65341	60589	4752	12046
R-sq	0.000	0.000	0.001	0.000

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

Table (**??**) shows the estimation for equation 17, on the sample period 2005-2019. The primary dependent variable is $\epsilon_{NetExposure,i,t}$ which is obtained from equation 16. All four columns include both $TD\text{-}VAR$ and $\widetilde{(TD)}$ as well as firm and sector fixed effects. Each column includes a different set of industries as the sample: (1) includes all industries, (2) excludes the utilities and energy sector, (3) only views the utilities and energy sectors, and (4) includes only the consumer discretionary and consumer staples sectors.

9 Figures

Figure 1: Google Search Volume Index (SVI) - U.S. average

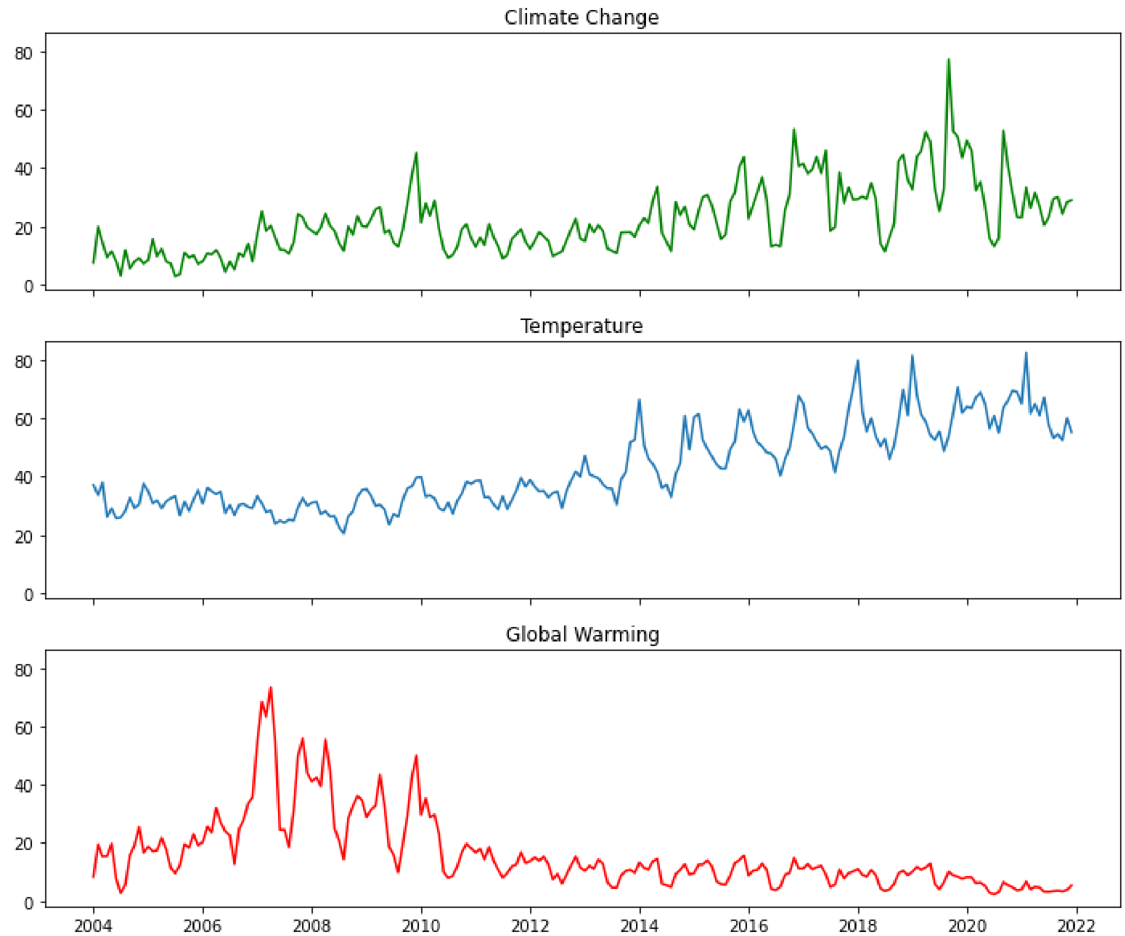


Figure (1) show the monthly U.S. average of 3 Google Trends indexes, respectively "Climate Change", "temperature" and "Global Warming". Each month, the U.S. index is computed as $US_m = 1/50 \sum_i^{50} G_{i,m}$. Given that in each state the index assume values between 0 and 100, the US index is the simple average of the relative search in each month. This is just for illustration porpouse given that in the analysis we employ state specific indexes.

Figure 2: Extremes realization and TD average value

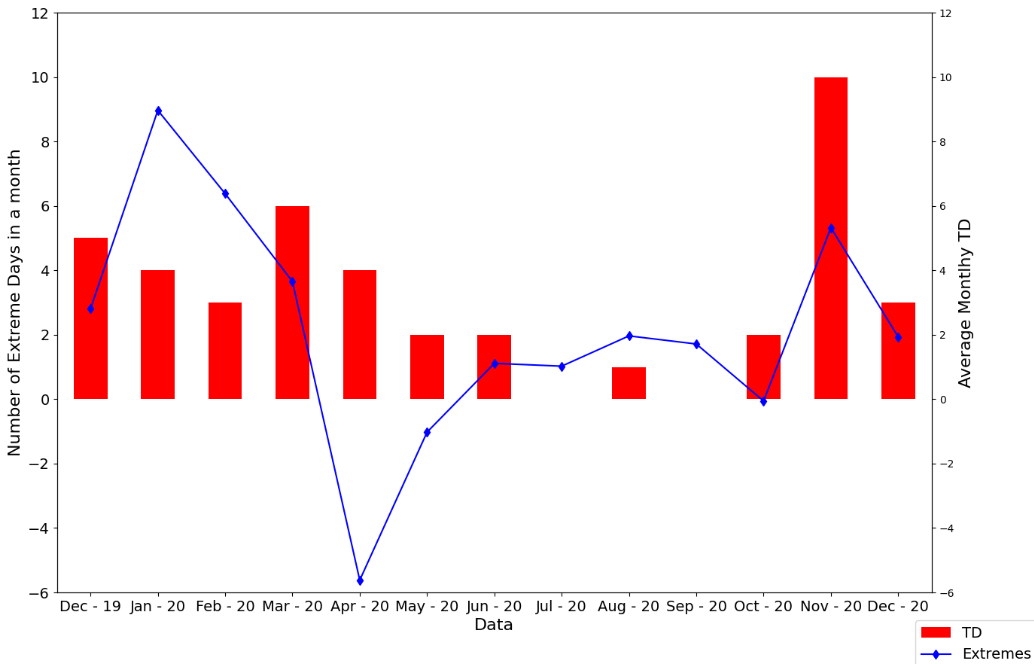


Figure (2) shows historical evidence of extreme realizations and monthly average temperature anomaly for the city of Boston in 2020. Red bars shows the number of day within a month the temperature experienced a an "extreme value", when the absolute value of temperature deviation higher than 2 standard deviations of historical distribution. The blue line shows the monthly average temperature deviation realization.

Figure 3: Effects on extreme, increase in TD and TDVAR

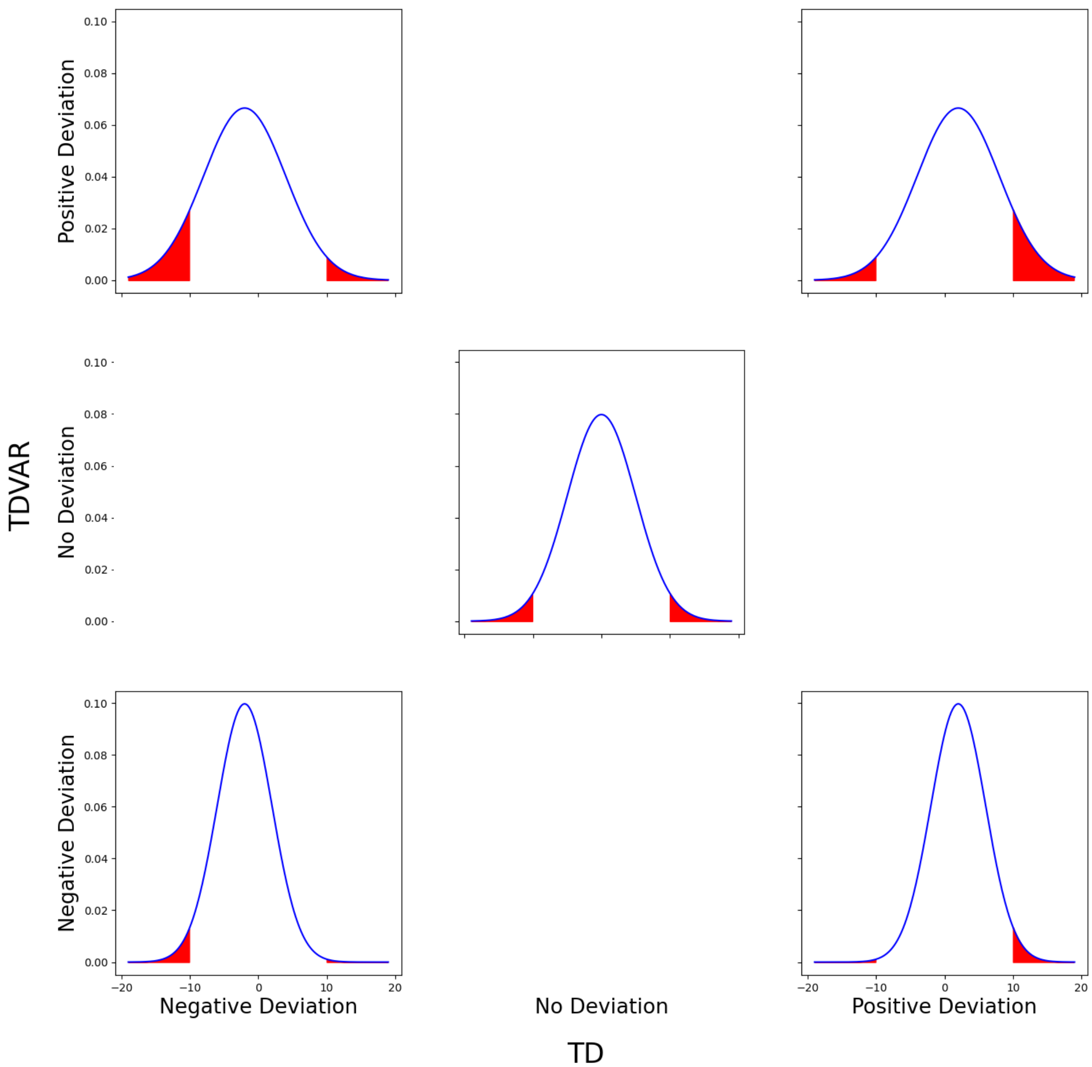
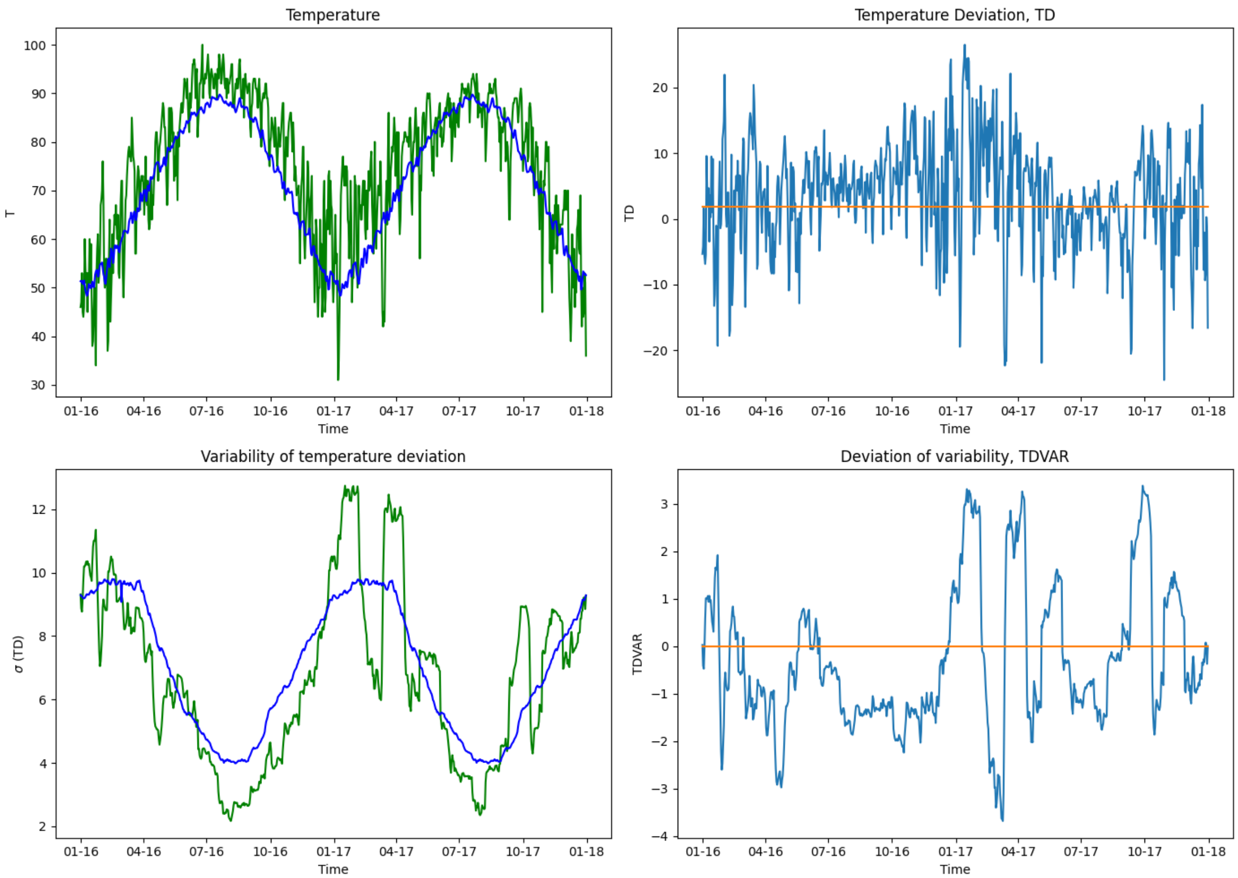


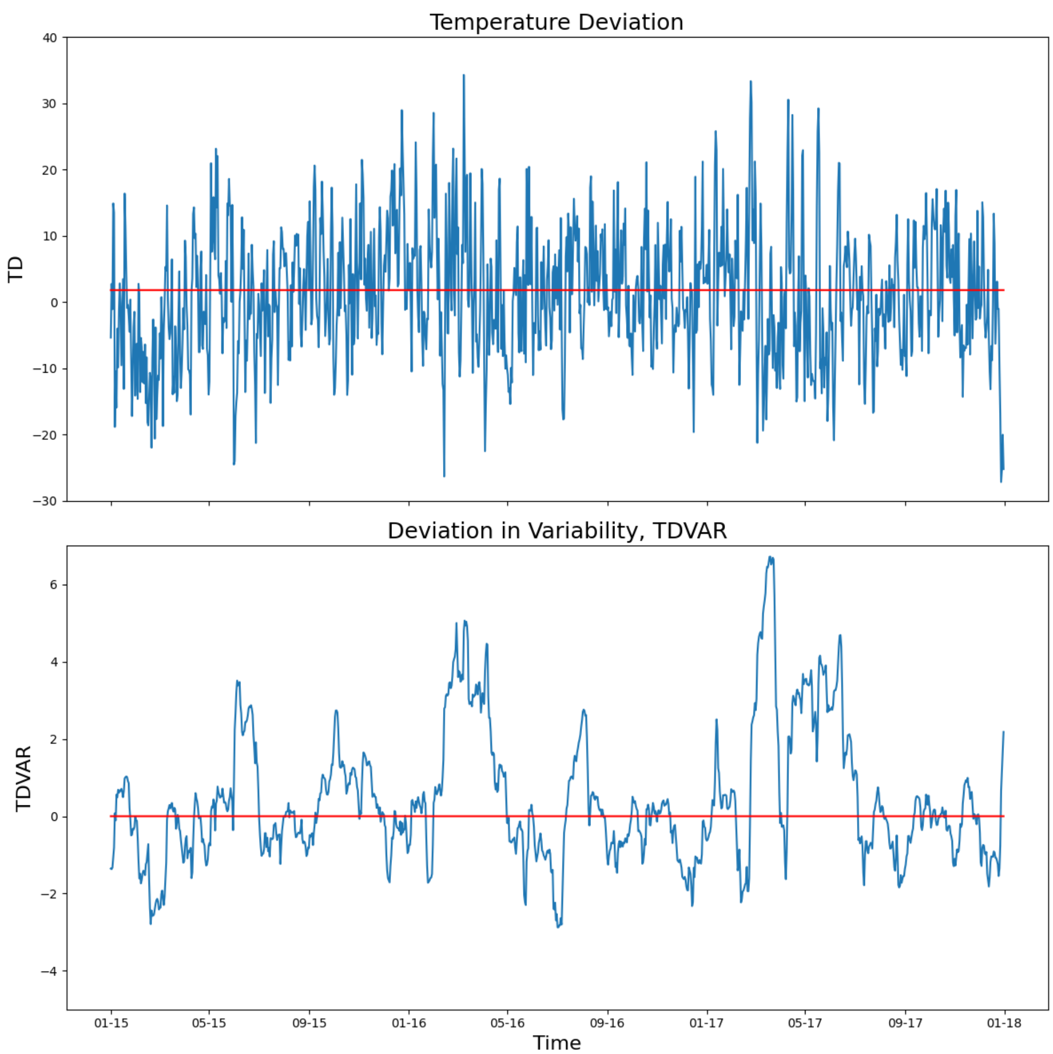
Figure (3) presents the interplay between increase in temperature deviation, TD, and deviation in variability, TDVAR. The columns entries present in the center, the historical level of TD that is equal to 0. The left-hand side column present a situation in which the average of $TD = +2$. The column on the left shows the situation in which the average of $TD = -2$. The entries on the rows show the comparable situation for TDVAR. The central rows, "Historical", present the situation associated with the historical variability level, $TDVAR = 0$. The Positive and Negative rows present respectively $TDVAR = 1, TDVAR = -1$. Red shaded area represent the probability of extreme, wit threshold set at $+10$ and -10 degrees.

Figure 4: TDVAR derivation for Atlanta



Represents the steps embraced to extract from the temperature level the various component analyzed in the work. The top left figure shows in green the Temperature level, T, as well as the historical average of the Temperature level, $\overline{T}$. These components characterize the right hand side in equation (1). The top right panel displays daily Temperature Deviation in blue, TD, that is the left hand side of equation(1). The bottom left figure shows in green the volatility of temperature deviation, $\sigma(TD)$, defined by equation (3) and in blue its historical level, $\overline{\sigma(TD)}$. These two components represent the right-hand side of equation (4), which outcome, TD-VAR, is shown in the bottom right figure, in blue.

Figure 5: TD and TDVAR characteristics



The figure shows temperature characteristics for Boston in year 2015, 2016, 2017. The top figures shows the daily temperature deviation, TD, defined in equation (1). The red line presents the average TD over the period, that equals $+1.8$°F. The bottom figure present the daily TDVAR computed on a monthly rolling window following equation(4).

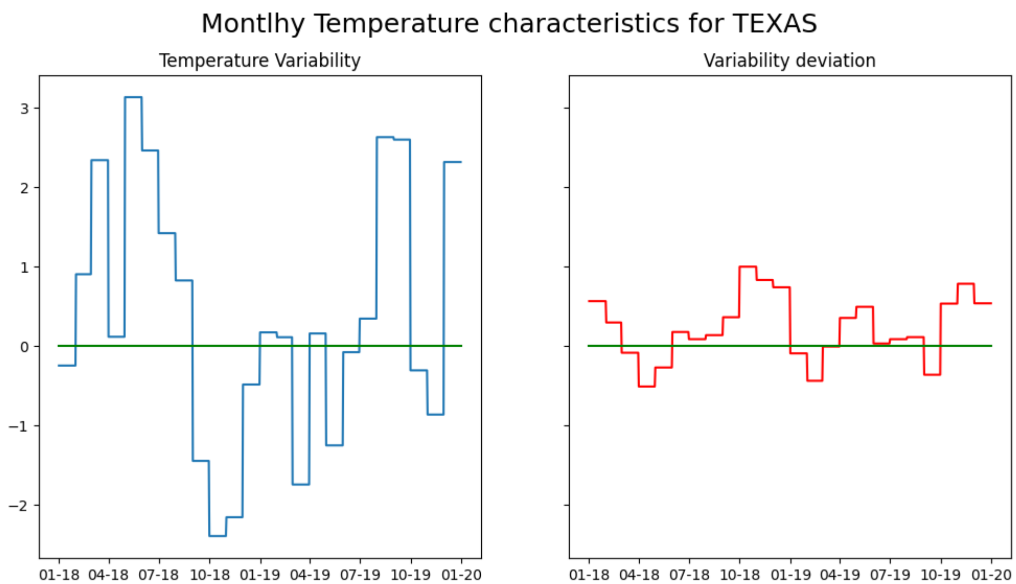


Figure 6: shows on the left panel monthly average temperature deviaton(TD 1) and on the right panel the monthly deviation in temperature variability ($TDVAR$, 4) for Texas between 2018 and 2020.

A State and country aggregation

In this appendix, we discuss in detail the aggregating methods we develop in Section (3.4) to aggregate temperature at the state and country level.

A.1 State aggregation

The first digression regards the state aggregating method. We employ this index to match two analyses. Firstly, from a financial perspective, we employ energy consumption and the cross-section of equity returns considering the firm's headquarter state. The objective is to replicate at the state level the indicator that represents the deviation from average temperature variability, $TD\text{-}VAR$ and allows the comparison with the state daily temperature anomaly, TD. For this purpose, we collect data at the grid level within U.S. space and assign each grid to a particular state.
We then define the state s temperature at day d as

$$T_{s,d} = \sum_{i=1}^{N_s} w_i * T_{i,d} \tag{18}$$

that is a weighted average of the temperature in the N_s grids within state s. Implementing this procedure we obtain a coherent measure at the state level with the one defined at the city level. Then, it is possible to proceed as in Equation (4) at the city level obtaining the day-to-day temperature anomaly, the day-to-day variability, and the deviation from average variability at the state level. We implement $w_i = \dfrac{1}{N_s}$ to obtain an equally-weighted state temperature level index. Alternative to the equi-weighting algorithm, it is possible to aggregate based are GDP or population weighted, that will be discussed in more details in the following section. Since we are dealing with temperature variability, aggregating an index or its variability could result in abnormal differences when the index components exhibits different behaviour[22]. Alternatively to Equation (18), there is the chance to directly aggregate state $TD\text{-}VAR$:

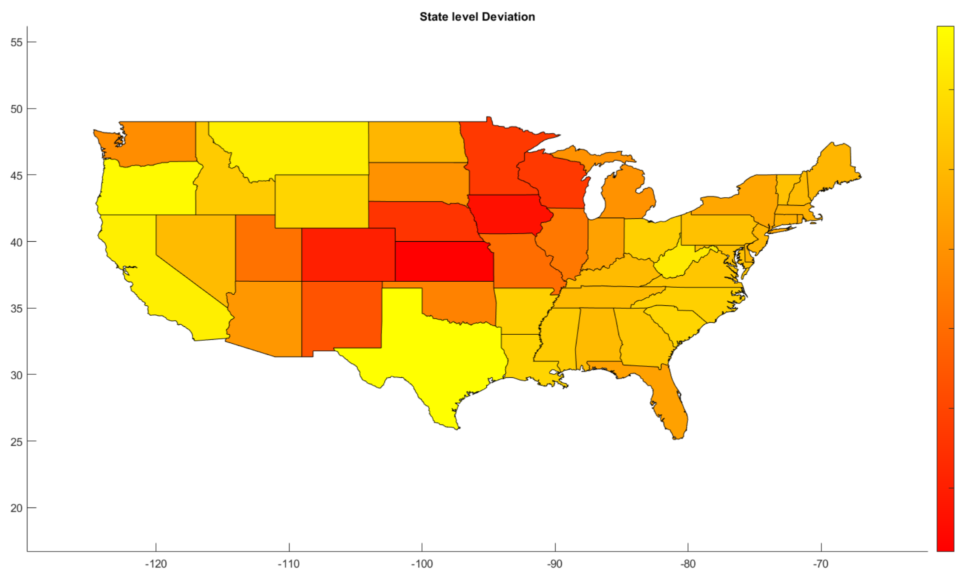
$$TD\text{-}VAR_{s,d} = \sum_{i=1}^{N_s} w_i * TD\text{-}VAR_{i,d} \tag{19}$$

In this way, the state-level index would represent the average deviation from historical temperature variability. Castellano et al. (2020) shows that even for temperature index aggregation, under suitable conditions, with the main being that T_s follows an AR(p) process, carefully selecting $\sum x_i^2 = 1$ in (18) the resulting index has the risk equal to weighted average of the single indexes risk. It is feasible to compare average risk coming from 19 and 18.
Another reason that allows us to aggregate temperature and not variability deviation is the number of cell grid within each state. We test possible differences employing city-level data at airport station[23] as temperature data and tested the differences coming from the different

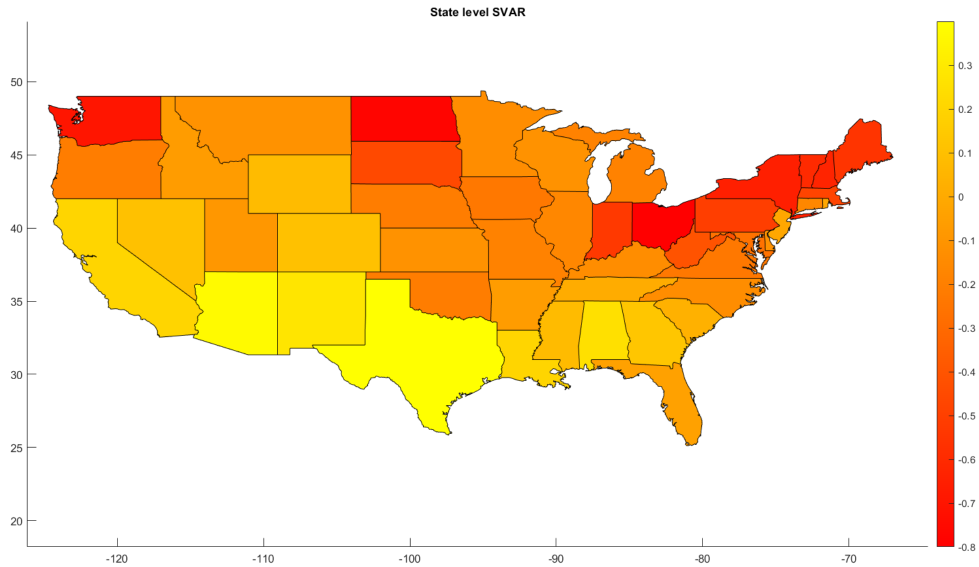
[22] $\sigma(\sum w_i * x_i) \neq \sum w_i * \sigma(x_i)$

[23] We enlarge the data set by Diebold and Rudebusch Diebold and Rudebusch (2019) considering all the airports within the U.S. From the NOAA, 330 airports have active data covering 1960 to 2017

aggregating procedures.
Comparing the state deviation variability coming from the aggregate temperature levels and the one coming from the aggregate deviation volatility itself, we find an overall correlation of 95% on the level. Some states exhibit lower values, such as California and Texas(but still close to 90%), and are the ones that present more airports in the data set.
We now analyze some characteristics and main differences between state monthly deviation in variability and the monthly temperature deviation. Figure ?? shows the cross-sectional difference for a particular month, September 2005. In the upper section, we plot the monthly state-level temperature deviation (TD) whereas in the lower panel we display the deviation in variability(TD-VAR).
It is possible to note that also at state levels the two measures exhibit different patterns. There are states, such as Texas, that show a high level in temperature deviation as well as a high deviation in variability. States very close to Texas, such as New Mexico and Arizona, display a higher level of deviation in variability (TD-VAR) but, concerning temperature deviation, the levels are among the smallest in the U.S.



Appendix Figure A1



Appendix Figure A2

Appendix Figure A3: shows empirical measurement of TD, figure A1, and $TDVAR$, Figure A2. The heatmap present in yellow states that are more exposed to the measure and in red states less exposed. The measures are refers to September 2015.

A.2 U.S. deviation in variability factor

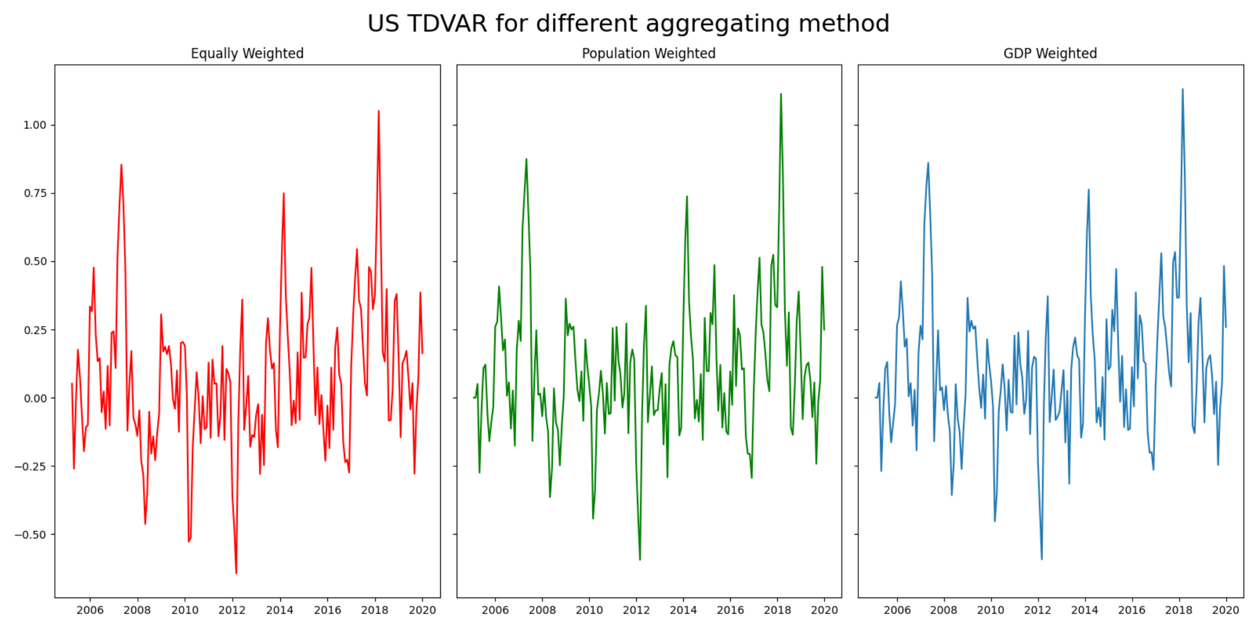
The next step we take is to derive a U.S.-wide TD-VAR factor, that could easily be seen as an aggregate level of the state volatility. Such a method would release the geographical characterization and give the possibility to match against indexes that are not geographically tightened but refers to the U.S. In this context, the aim is to disentangle U.S. TD against U.S. TD-VAR and hence, considering the two possible approaches employed at state level, 18 and 19 and that each state can be seen as a single cell, at this stage we build U.S.-wide TD and TD-VAR with 19, defining

$$US_{TD,m} = \sum_{i=1}^{N_s} w_i TD_{i,m} \tag{20}$$

$$US_{TD\text{-}VAR,m} = \sum_{i=1}^{N_s} w_i TD\text{-}VAR_{i,m} \tag{21}$$

However, aggregation at the U.S. level poses a second problem. regarding the weights associated at each state temperature deviation and deviation in variability. Following what we did with aggregation at state level, the natural solution would be to employ an equally weighting method, $w_i = \dfrac{1}{N_s}$.
In such a way however, an high TD-VAR in small state would have the same impact as the

one experienced by a larger one, in the final index. The weighting method should thus reflect the importance each state exhibits in the nationwide index.
The two natural possibilities are GDP– and population-based weight. Both measures are not available at monthly frequency, with the former defined quarterly and the latter yearly, so we forward feed the data series to obtain monthly frequency series comparable with TD-VAR and TD, as described in Section XX.
Employing the first approach, with GDP-weight, would imply a relative importance of the most productive areas, meaning an economic specific impact of TD and TD-VAR. Applying the second approach instead would gather an attention to what people perceive: more variability in a densely populated state is more important than the same event in a state less populated.
Figures A4 shows the difference in the U.S.-wide index for TD-VAR according to the different weighting criteria. When comparing the three measures however there are minor differences just when considering equally weighting against population or GDP.



Appendix Figure A4: shows three main index construction based on different weighting method of $us_t = \sum_i w_i * tdvar_{i,t}$ in the year 2005-2020. The left panel show equi-weighted index construction where $W_i = 1/N_i$ with $N_i = 50$. The central panel shows the population based weighting method where $w_i = pop_{i,t}/\sum_i pop_{i,t}$. In the right panel is plotted the US wide index weighted for state GDP, defining $w_i = \dfrac{GDP_{i,t}}{\sum_i GDP_{i,t}}$