# Nailing Down Volatile Temperatures

## Examining their Effects on Asset Prices

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# Motivation & Research Question

# Global supply chains face months of disruption from Texas storm

Manufacturers hit by shortages as petrochemicals plants remain below capacity

Figure: Financial Times, March 24th, 2021

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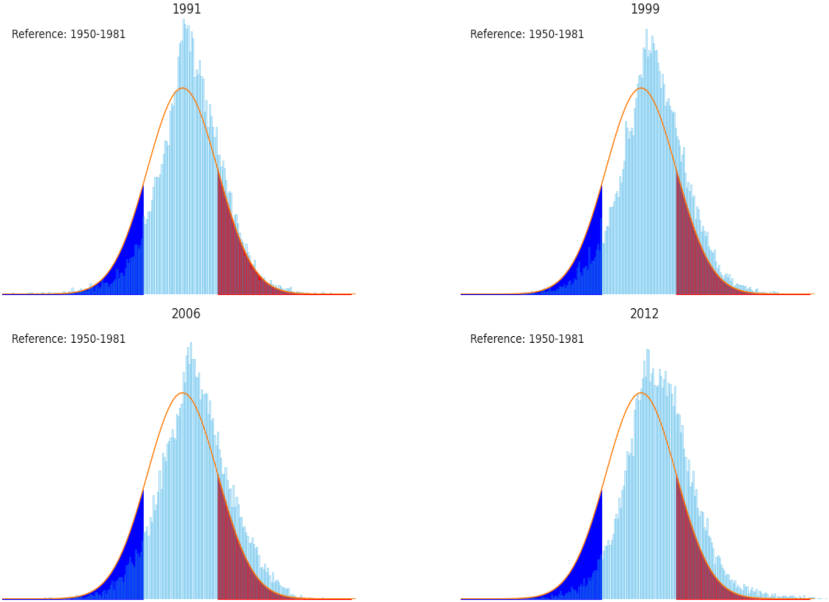
# Northwest Heat Wave Triggers Blackouts as New York Will Sizzle

- Avista instituted rolling power outages on Monday and Tuesday
- East coast cities now face their own heat wave beginning today

Figure: Bloomberg, June 29th, 2021


1991
Reference: 1950-1981
1999
Reference: 1950-1981
2006
Reference: 1950-1981
2012
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# Motivation: Temperature anomalies

Analysis of temperature anomalies on firm performance

- Extreme temperatures affects firms earning (Addoum et al., 2020).
- Stock return sensitivity to abnormal temperature (Kumar et al., 2019).
- Network contagion effect from temperature extreme (Pankratz and Schiller, 2021).

Emerging literature relates variability in temperature anomalies to economic aggregate and corporate performance

- Agriculture: crop-yields (Wheeler et al. (2000), Celgar et al. (2016))
- Human health and mortality (Zanobetti et al (2012))
- Economic growth (Donadelli et al (2017), Kotz et al (2021))
- Asset prices (Makridis and Schloetzer (2021))

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# Research Questions

We investigate the changing distribution of temperature anomalies and their associated impacts on financial and economic outcomes.

We ask the following...

- How to generally represent the changes in the distribution of temperature anomalies spatio-temporally?
- Is the statistic material to energy and weather markets over and above temperature anomalies?
- Does differential exposure to changing temperature anomalies affect stock prices?
- Are these shocks drivers of investor attention and beliefs or do they cause adverse disruptions to firm operations?

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# *TD-VAR*

# Long Term Volatility

How to generally represent the changes in the distribution of temperature anomalies spatio-temporally?

- Kotz et al., 2021: Day-to-day Temperature Variability

$$\widetilde{T}_{r,y} = \frac{1}{12} \sum_{m} \frac{1}{\sum_x w_{r,x}} \sum_{x} w_{r,x} \sqrt{\frac{1}{D_{m,y}} \sum_{d} (T_{x,d,y} - \overline{T}_{x,d,y})^2} \tag{1}$$

- Donadelli et al., 2019: Temperature Volatility Shocks

$$TVOL = |\sigma_y - \overline{\sigma}_h| \tag{2}$$

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# *TD-VAR* Definition

For a location $s$, we define the daily temperature anomaly is:

$$TD_{s,d} = (T_{s,d} - \overline{T}_{s,d}), \tag{3}$$

the monthly $m$ average temperature anomaly is:

$$\widetilde{TD}_{s,m} = \frac{1}{D_m} \sum_{d=1}^{D_m} TD_{s,d}, \tag{4}$$

while the variability of temperature anomaly:

$$\sigma(TD_{s,m}) = \frac{1}{D_m} \sqrt{\sum_{d=1}^{D_m} TD_{s,d}^2}. \tag{5}$$

and the monthly deviation of temperature variability

$$TD\text{-}VAR_{s,m} = \sigma(TD_{s,m}) - \overline{\sigma}(TD_{s,m}), \tag{6}$$

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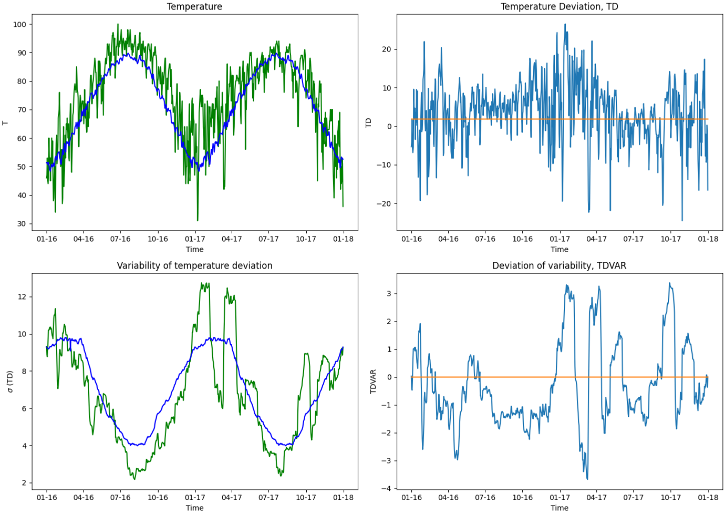
# Motivation: stylized temperature characteristics



# Intuition behind *TD-VAR*

- Thresholds are commonly used to represent the occurrence of extreme temperatures when using $\widetilde{TD}$.
- However, positive values of $\widetilde{TD}$ do not necessarily imply an increase in the occurrence of extremes.
- Changes to *TD-VAR* characterize shifts in the entire distribution of temperature anomalies.
- Theoretically, the probability of experiencing extremes is computed through the equation:

$$X_{TD} = \int_{k_{max}}^{\infty} \psi(x)dx + \int_{-\infty}^{k_{min}} \psi(x)dx. \tag{7}$$

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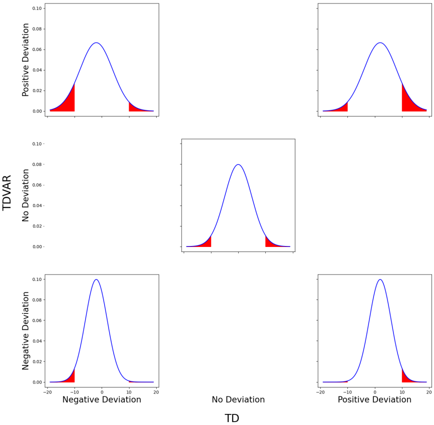
# TD TD-VAR and extremes

Figure: Effects on extreme, increase in TD and TDVAR



# Geographical aggregation

As we deal with geospatial data, we use two datasets:

- City Level Data: NOAA Global Historical Climatology Network daily (GHNCd).
- State Level: BEST database, spatially homogeneous. We derive state *TD-VAR* by:

$$T_{s,d} = \sum_{i=1}^{N_s} w_i * T_{i,d} \tag{8}$$

with $w_i = 1/N_s$

# Validation Exercises

# Electricity demand 1/2

Are changes in $TD - VAR$ material to energy and weather markets over and above $\widetilde{TD}$?

- Weather conditions are drivers of energy consumption (Quayle and Diaz, 1980, Chang et al., 2016).
- We employ monthly data from EIA to match state temperature statistics.
- We forecast future energy demand employing ARMA (J, P) model:

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

- Analyze whether the unexpected energy consumption, $\epsilon_{s,t}$, is driven by temperature statistics:

$$\epsilon_{s,t} = \beta_1 * TD\text{-}VAR_{s,t} + \beta_2 * \widetilde{TD}_{s,t} + \gamma_t + \eta_n + \epsilon. \quad (10)$$

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# Electricity demand 2/2

Table: Estimation Results for energy consumption

| | Residential | Commercial | Industrial | Total |
|---|---|---|---|---|
| *TD-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

# Weather derivatives 1/2

- Weather derivatives allows for the hedging of volumetric risk, e.g. declining sales in the energy and power sector due to weather.

$$CDD_{i,m} = \sum_{d=1}^{D_m} (T_d - T_0, 0)^+ \qquad HDD_{i,m} = \sum_{d=1}^{D_m} (T_0 - T_d, 0)^+$$

where $T_0$ is set at 65F for futures traded at CME.

- We check the association of monthly levels of CDD and HDD to temperature statistics:

$$\begin{aligned} CDD_{s,m} &= \beta_t T_m + \beta_e \widetilde{TD} + \beta_v TD\text{-}VAR + \beta_v \sigma(TD) + \epsilon \\ HDD_{s,m} &= \alpha + \beta_t T_m + \beta_e \widetilde{TD} + \beta_v TD\text{-}VAR + \beta_v \sigma(TD) + \epsilon \end{aligned} \tag{11}$$

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# Weather derivatives 2/2

Table: 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-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) |
| $\alpha$ | | | 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

# Empirical analysis

# Firm Specific Temperature Exposure

Does differential exposure to changing temperature anomalies affect stock prices?

- We use the Russel 3000 index, 99.8% market cap for firms located in U.S.
- *TD-VAR* for firm $i$ is chosen considering headquarter state.
- Specifically, we estimate the following model

$$r_{i,t,s} = \alpha + \beta_T * T_{t,s} + \beta_1 C_{i,t-1} + \phi_t + \eta_i + \epsilon_{i,t} \quad (12)$$

where T is a generic term for $\widetilde{TD}$ and *TD-VAR*; $C_{i,t}$ are control variables for firm profitability & riskiness

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# Firm Specific - Results

Table: Estimation for *TD*(A) and *TD-VAR*(B) on stock return

| 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) |
| 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) |
| 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

# Persistence

Table: 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 |

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# Spatial Long-Short Portfolio

- We examine whether investors can reduce their exposure to temperature by focusing on local temperature information.
- Sort states into quintiles based on their $\widetilde{TD}$ and *TD-VAR* exposure.
- Form long–short spread portfolios: going long in the portfolio of less-exposed states and short in the most-exposed states.
- Project the 5 portfolio returns on the Fama-French 3 factors and a fourth momentum factor.
- The $\alpha$ for each portfolio captures whether this is a viable hedging strategy.

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- Project the 5 portfolio returns on the Fama-French 3 factors and a fourth momentum factor.
- The $\alpha$ for each portfolio captures whether this is a viable hedging strategy.

# Spatial Long-Short Portfolio

Table: Returns to Portfolio Sorted on *TD-VAR* and $\widetilde{TD}$, Energy, Utilities, Consumer Staples, Consumer Discretionary

| | Panel A: *TD-VAR* | | | Panel B: $\widetilde{TD}$ | | |
|---|---|---|---|---|---|---|
| | **Excess Return** | **3-factor** | **4-factor** | **Excess Return** | **3-factor** | **4-factor** |
| Quintile 1 | 1.114*** | 0.435*** | 0.439*** | 0.881** | 0.213 | 0.214 |
| | (3.172) | (2.415) | (2.388) | (2.518) | (1.200) | (1.201) |
| Quintiles 2–4 | 0.7253*** | 0.162 | 0.16 | 0.755*** | 0.185 | 0.182 |
| | (2.833) | (1.473) | (1.446) | (2.888) | (1.611) | (1.586) |
| Quintile 5 | 0.678** | 0.055 | 0.050 | 0.946** | 0.293 | 0.298 |
| | (2.191) | (0.333) | (0.308) | (2.782) | (1.569) | (1.601) |
| (1–5) | 0.436 | 0.38 | 0.389 | -0.058 | -0.08 | -0.084 |

# Channels of Price Reaction

# Identifying channels of price reaction

Are these shocks drivers of investor attention and beliefs or do they cause adverse disruptions to firm operations?

- The prior analysis suggests that exposure to *TD-VAR* has serious implications for firm stock prices.
- We don't observe the exact mechanism that dictates financial consequences.
- Two possible vectors at play:
  - Investors belief: heightened temperature variability acts as a "wake-up call".
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# Attention

- Engle et al., 2020 represent climate uncertainty through WSJ news, U.S. country wide.
- Granular representations of climate attention could capture the geographical heterogeneity of *TD-VAR* and $\widetilde{TD}$.
- Obtain Google Search Volume Index (SVI) for "Temperature" and "Climate Change" for each state.
- Following Choi et al., 2020, we regress unexpected state-level SVI for each topic on the temperature statistics.

$$\epsilon_{SVI,s,t} = \beta_T * TD\text{-}VAR_{s,t} + \beta_D * \widetilde{TD}_{s,t} + \rho_t + \gamma_s + \epsilon_{s,t}. \quad (13)$$

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# SVI results

Table: State specific Google SVI AR(1) residual

| | Climate Change: Panel (A) | | | Temperature: Panel (B) | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 1 | 2 | 3 |
| *TD-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

# Firm-level impact beyond attention

- We analyze the realized impact of temperature shocks on firm-level operations.
- Sautner et al., 2020 develop a time-varying measure of firm-level exposure to physical climate change risks.
- We disentangle material impact of the temperature shock from the effects of attention:

$$PhysCCExp_{i,t} = \alpha + \beta_1 * WSJt + \beta_2 * \epsilon_{WSJ,t} + \gamma_i + \epsilon_{NetExp,i,t}. \quad (14)$$

- $\epsilon_{NetExposure,i,t}$ contains the concrete impact of physical climate change exposure beyond attention, we regress against temperature statistics:

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# Results

Table: Firm-Level Exposure to Temperature Shocks

| | (1) All Industires | (2) Ex Util/Energy | (3) Util/Energy | (4) Cons Disc/Staples |
|---|---|---|---|---|
| *TD-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

# Conclusions

- We analyze a temperature metric, *TD-VAR*, the deviation of the average temperature variability from its historical level.
- We show that *TD-VAR* is a driver for unexpected energy consumption especially for the residential and industrial sectors.
- Traders consider *TD-VAR* in the pricing of weather derivatives.
- In U.S. stock markets, Energy, Utility, and consumer sectors are geographically impacted by *TD-VAR*.
- The pricing effect is due to both investor attention and firm-level repercussions as a result of changes to *TD-VAR* rather than $\widetilde{TD}$.

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