Increasing Extreme Summer Hot Days Contribute to U.S. Stock Market Volatility

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Abstract

The response of temperature extremes to warming is a key climate impact, but remains uncertain at the local level. Further, the impact of extreme heat on investments is debated. This study addresses both challenges. Using weather reforecast data, we analyze how regional mean temperature changes influence the local frequency of summer days exceeding the 95th percentile of maximum temperatures across the continental US. We then map firm-level facility locations to evaluate the sensitivity of publicly traded companies to warming. In a panel model, the summer extreme heat probability has a statistically significant positive impact on equity volatility. Companies exposed to more frequent extreme heat events due to regional temperature anomalies tend to exhibit increased volatility. The baseline regression suggests that the warming trend alone led to an increase of 6.6% (72 basis points) in total market volatility over 2001-2020, highlighting that warming is a material factor driving market uncertainty.

Main

Climate change is increasingly recognized as an important factor influencing economic growth and financial markets. Global average temperatures have risen by over 1 °C since the preindustrial period, and each year between 2015 and 2024 ranks among the ten warmest ever recorded (Copernicus Climate Change Service 2024). Extreme heat events have also increased in frequency, intensity, and duration (Perkins, Alexander, and Nairn 2012; Perkins-Kirkpatrick and Lewis 2020), causing direct impacts on productivity, health, agriculture, wildfire risk, and infrastructure (Hsiang et al. 2017; Abatzoglou and Williams 2016). It is critical to understand how the rising prevalence of extreme heat impacts businesses and financial markets. There is evidence that markets do not efficiently

price climate risk (Hong, Li, and Xu 2019), and more research is needed to clarify and monitor the risk climate change poses to the financial system (Brunetti et al. 2021).

While heat extremes are broadly expected to increase (Climate Change 2014), differential frequency of extremes is apparent across latitudes, and feedback mechanisms like snow and ice-temperature feedbacks and soil drying trends can amplify heat extremes (Simolo and Corti 2022; Vogel et al. 2017; Lewis et al. 2019). It is difficult to quantify the sensitivity of local temperature extremes to mean warming given the limited observational record and regional climate variability. However, several studies demonstrate that the increased frequency of hot extremes is largely explained by a shift of the surface temperature distribution by the local mean warming (Patel, Bonan, and Schneider 2024; Loikith and Neelin 2015; Rhines and Huybers 2013). This work takes an alternative approach, utilizing reforecast data to characterize the sensitivity of local heat extremes to regional warming over the United States.

The specific implications of extreme heat for financial markets remain underexplored. Much of the existing literature focuses on aggregate economic impacts, for example estimating the future costs of temperature increases across a number of sectors and the impact on GDP, finding overall negative effects in the southern US and positive GDP changes in the Pacific Northwest and New England (Hsiang et al. 2017).

Despite the relevance for investors, there is limited research and little consensus on the direct effect of heat on firm financial performance. In a study of 13,000 firms from 1995 to 2019, incremental exposure to extreme heat reduced revenues, and greater heat exposure was associated with larger discrepancies between analyst estimates and real earnings as well as worse earnings announcement returns (Pankratz, Bauer, and Derwall 2023). Hosseini 2024 also report that exposure to heat anomalies has a negative impact on earnings in five industries within the Fama and French classification. Other results are mixed: no relationship was found between heat exposure and establishment-level sales in the US from 1990-2015 (Addoum, Ng, and Ortiz-Bobea 2020), while another study identified bi-directional impacts of extreme temperature on earnings in over 40% of industries in the US (Addoum, Ng, and Ortiz-Bobea 2023). From a market perspective, Peillex et al. 2021 found that between 1995 and 2019, trading volumes declined by 4-10% in the French stock market when maximum temperatures exceeded 30°C in Paris. Developing a fuller understanding of how extreme weather phenomena impact returns would enable investors to integrate climate considerations in the investment process.

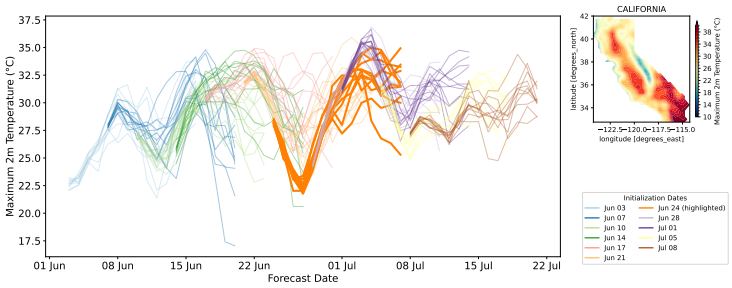
We present a new empirical approach to examining how heat exposure affects U.S. stock market performance. First, we analyze the relationship between regional summer mean temperatures and the probability of exceeding the local extreme temperature threshold (maximum temperature above the 95th percentile) in the continental United States. Reforecast data provides additional physically possible temperature trajectories for a given set of large-scale conditions, allowing us to quantify the sensitivity of temperature extremes to region-mean warming with improved statistical robustness. We then test whether company

exposure to locations with higher extreme heat sensitivity impacts their stock volatility over 2001-2020. This work conveys the financial materiality of heat exposure to companies and investors and can inform resilience measures.

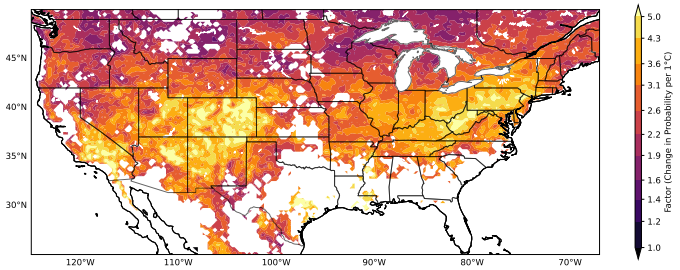
0.1 Using reforecast data to estimate extreme heat sensitivity

This study takes a novel approach to quantifying trends in extreme heat by using the European Centre for Medium-Range Weather Forecasts (ECMWF)'s Integrated Forecasting System (IFS) reforecast dataset. These datasets consist of forecasts for past dates over the last 20 years, produced with the same model used for real-time forecasts, ensuring consistency and comparability.

Reforecast data are especially useful in the zone between short-term weather forecasts and long-term climate projections. While weather forecasts depend on accurate initial conditions and climate forecasts rely on boundary conditions, reforecasts capture aspects of both. In this intermediate range, large-scale flow patterns may still respond to initial conditions and boundary forcing, even if individual weather events are not predictable (Hamill, Whitaker, and Mullen 2006). By comparing past forecasts with observations, reforecast datasets support model calibration and provide a reliable basis for analyzing trends in complex systems.



(a)



(b)

Figure 1: The timeseries (top plot) presents the evolution of the maximum 2-meter temperature (°C) in the reforecast dataset for the hindcast year 2001 over California (inset), illustrating the progression of ensemble members across different initialization dates. Each line represents a forecast trajectory from lead day 0 to lead day 12. At lead day 0, ensemble members exhibit minimal spread, indicating strong agreement among forecasts. However, as lead time increases, the spread widens, reflecting growing uncertainty and reduced dependence on initial conditions. The highlighted time series corresponds to the forecast initialized on June 24. Figure 1b depicts the multiplicative factor by which the probability of exceeding extreme temperatures (defined as the climatological 95th percentile) changes with an increase in regional temperature. The regional temperature is averaged over an approximate 1000 km radius for each grid point, providing insight into the sensitivity of extreme temperature exceedance probabilities to broader temperature variations.

To capture summer variability from 2001 to 2020, eleven dates were chosen between June 15 and July 20. These dates correspond to the 12th-day lead from each initialization date. This choice is based on the observation that forecasts at this lead time have a relatively high spread and are less dependent on the initial conditions, improving the robustness of our analysis (Fig. 1a). Each date includes 11 ensemble members, producing 121 weather scenarios per year and

2,420 in total over the 20-year period.

This large ensemble allows us to explore a broad range of possible temperature outcomes at each grid point, ensuring a statistically robust dataset for analyzing extreme temperature probabilities and trends. By leveraging this expanded dataset, we can better quantify the variability and predictability of extreme temperature events under different climate conditions.

At each grid point, we examine how the probability of exceeding the climatological 95th percentile threshold for extreme temperatures changes in relation to a climate change indicator, in this case regional temperature anomalies. This relationship is useful because, if it holds across both shorter (interannual to decadal) and longer (multi-decadal) timescales, it may allow us to infer externally-driven trends in extreme event probability. We relate the changes in exceedance to regional temperature anomalies because warming projections are more robust across models at the regional scale than the local scale, and regional changes scale linearly with global mean surface warming in most regions (Diez-Sierra et al. 2023). Linking local summer temperature extremes to region-mean warming could therefore enable more accurate estimates of future changes in extreme heat across the United States.

Figure 1b highlights strong spatial differences in extreme heat sensitivity: over much of the U.S., the probability of extreme heat events more than doubles with each additional degree of warming, and in several places the change increases by a factor of 5 or higher. The Ohio Valley (including Ohio, West Virginia, Kentucky, and Pennsylvania) and the Mountain West (including Colorado, New Mexico, Arizona, and Utah) stand out in Fig. 1b as large coherent regions with high summer extreme temperature sensitivity (4x increases in probability). This result is consistent with previous conclusions (Loikith and Neelin 2015). In these regions, the probability distribution function (PDF) of temperature has a short warm-side tail, such that a mean shift in the distribution due to warming causes a greater increase in fixed-threshold exceedances compared to a Gaussian distribution (Loikith and Neelin 2015). Southern California and parts of the Gulf Coast, including southeastern Texas and Louisiana, also have sensitivity factors above 4. These spatial patterns offer valuable insight into where the risk of extremes is accelerating most rapidly.

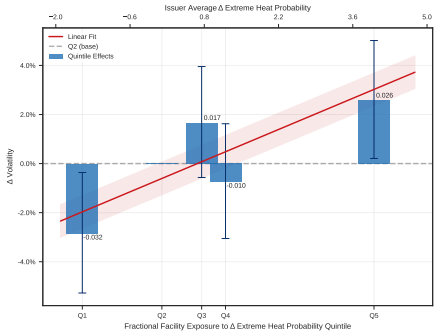
0.2 Linking heat risk to companies and financial performance

We analyzed the effect of regional temperature anomalies and firm-level heat sensitivity on US equity returns using a 20-year panel dataset. Firm-level equity returns were modeled as a function of regional temperature anomalies (time- and space-varying), firm-level heat sensitivity (spatially varying), and their interaction term. Regional temperature anomalies were calculated as the deviation from the 30-year mean (1961-1990) over the land area within a 1000 km radius of each facility, and averaged at the firm level. The heat sensitivity, as described in the previous section, is a measure of how the probability of summer heat events changes with regional temperature anomalies, based on the geographic

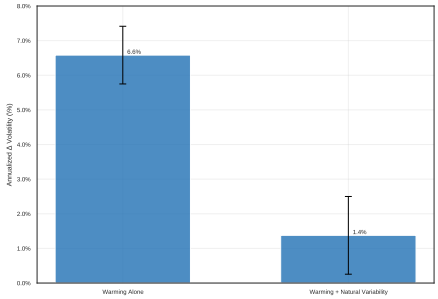
distribution of its facilities. We also modeled the impact on forward-looking analyst earnings revisions, which indicates the analysts' views of a company's fundamentals and often drives stock price movements.

To isolate the effects of climate variables, we controlled for a range of systematic risk factors using the 16 industry-standard Barra factors, which capture exposures to size, value, momentum, and other financial characteristics. In addition, we accounted for unobserved, time-invariant firm-specific characteristics through firm-level fixed effects, and we controlled for macroeconomic shocks and other time-varying influences using time fixed effects.

The interaction between regional temperature anomalies and heat sensitivity was a key focus, as it allowed us to assess how firms with different levels of heat sensitivity respond to temperature fluctuations. Our findings indicate that firms with higher heat sensitivity experience greater stock price volatility during periods of elevated regional temperature anomalies. Over the 20-year period, after accounting for natural climate variability, the cumulative impact of this interaction resulted in an estimated annualized increase in volatility of 72 basis points, corresponding to 6.6% increase from the sample period average. The model of forward-looking analyst revisions also reveals a statistically significant relationship with this interaction term, suggesting this is an important but unaccounted for driver of company's earnings prospects.



(a) The relationship between extreme heat probability and its impact on equity volatility. The bar graph represents the impact to volatility as a function of the fraction of facilities within quintile exposure bins. The linear relationship represents the impact of issuer average extreme heat probability on volatility with the shaded region indicating the 95% confidence interval. Firms with higher extreme heat probability (positive values on the x-axis) experience larger increases in volatility.



(b) Comparison of the impact of warming and natural variability on annualized volatility over the study period. The warming impact on annualized volatility is 6.6%, while the total impact including natural variability return is 1.4%, indicating a 72 and 16 basis point volatility increase at the mean respectively. Error bars represent standard deviation.

Figure 2: The impact of extreme heat probability on equity volatility. Panel (a) illustrates the partial effect of extreme heat probabilities on volatility, highlighting two distinct regression forms. Panel (b) compares warming and warming and natural variability impacts on annualized volatility over the time period of assessment, quantifying the financial impact of warming-driven equity uncertainty.

Kruttli, Tran, and Watugala 2025 also link climate risk to stock volatility increases, in that case for companies with facilities in the path of a hurricane. While extreme heat tends to draw less attention and cause less infrastructure damage than tropical cyclones, this analysis demonstrates that it has a similar, albeit smaller magnitude, effect on the stock market. Unlike hurricanes, extreme heat has a broad geographic scope, and may represent a more pervasive risk for companies.

Discussion

This study reveals substantial heterogeneity in the local sensitivity of summer heat extremes to regional warming over the continental US, with impacts on stock price volatility. In particular, the Ohio Valley, the Mountain West region, and Southern California stand out as hotspots, with amplified increases (4x)

in the frequency of hot extremes for a given regional mean warming. More broadly, in all locations where the effect is statistically significant, the increase in extremes outpaces the increase in the mean. The results reinforce previous studies (Loikith and Neelin 2015; Patel, Bonan, and Schneider 2024), enhancing confidence in the quantification of local extreme temperature sensitivity. Reforecast data is a valuable resource for evaluating changes in the probability distribution of climate variables, complementing reanalysis data and GCMs.

We examine the relationship between summer extreme heat probability and daily equity volatility over the second half of the year (July-December). The persistent effect of summer heat exposure on subsequent volatility suggests extreme temperature represents a systematic risk factor that amplifies market uncertainty. Companies more exposed to this hazard based on their facility locations exhibit greater volatility, indicating higher risk from an investment perspective. The conclusion is also supported from a fundamental perspective, by the spread in future analyst earnings estimate revisions. Our findings indicate market inefficiency in pricing extreme climate risks, particularly in forward-looking valuations. The increased volatility may reflect that investors face heterogeneous information sets about direct, indirect, and higher-order effects of extreme heat on corporate performance. These results highlight opportunities for more sophisticated measurement of firm-level heat exposure and more accurate pricing of climate adaptation benefits.

This study quantifies the financial impact of heat based on empirical, rather than theoretical or forecast, relationships. To our knowledge, this is the first study to estimate the effect of historical warming on the US stock market. The results align with related work demonstrating that extreme heat has had a discernible effect on market activity in recent decades (Peillex et al. 2021). For the firms with the highest extreme heat sensitivity across their facilities, a 1-degree regional warming anomaly is associated with approximately 2.8% increased daily volatility (Fig 2a). This suggests that issuers exposed to heat extremes would see financial benefits from improving resilience to extreme heat, including considering extreme heat exposure in facility planning. Future work could diagnose the channels of impact across industries, which we speculate could include impacts on labor productivity, cooling costs, consumer demand, and transportation. By demonstrating the historic impact of warming on the US stock market, this study motivates further research to explore how other climate risks may influence market dynamics, including over the seasonal cycle and across global geographies and markets. As climate change continues to affect weather patterns, understanding its impact on forward-looking financial indicators is crucial for developing robust investment strategies and enhancing corporate transparency regarding climate risk exposure.

Methods

Estimating extreme heat sensitivity

The ECMWF reforecast dataset used in this study is based on IFS model cycle CY47R2. It includes an 11-member ensemble, initialized twice weekly at 0000 UTC for start dates between June 3 and July 8. Covering the period from 2001 to 2020, each forecast extends over a 14-day lead time at a horizontal resolution of 0.25°× 0.25°. The atmospheric component runs at a TCo639 resolution with 137 vertical layers and is coupled with the Nucleus for European Modelling of the Ocean (NEMO) v3.4, which has 75 vertical levels and a horizontal resolution of 0.25°.

At each grid point we estimate how the probability of exceeding the climatological 95th percentile threshold for extreme temperatures changes in relation to regional warming. We first estimate the year-to-year variability in the probability of exceedance, then perform a regression of these probabilities against summer regional temperature anomalies at each grid point to quantify how risk evolves with regional warming. To make these results more interpretable, we express the relationship as the factor change in the probability of exceeding the extreme temperature threshold per 1°C increase in regional temperature (Fig. 1b).

Panel Model and Impact Assessment

By mapping the reforecast results (Figure 1b) to company facilities, we assessed the summer heat exposure of companies with over 90% of their facilities within the continental US. This linkage helps in understanding how and if companies are vulnerable to increasing extreme summer temperatures due to climate change.

In our analysis, the regional temperature anomaly is defined relative to a long-term baseline calculated from the period 1961–1990. That is, for each region we compute the average summer mean temperature over the baseline period and then derive the anomaly as the deviation of the observed temperature from that baseline. Formally, if T_{it} denotes the observed temperature for region i at time t and $\overline{T}_{i,1961-1990}$ is the corresponding baseline average, then the regional temperature anomaly is defined as

$$\Delta T_{it} = T_{it} - \overline{T}_{i,1961-1990}\,.$$

Our regression specification for July-December (H2) volatility is formulated as:

$$V_{it}^{H2} = \alpha + \beta\, T_{it} + \gamma\,(T_{it}\, S_{it}) + \delta\,(T_{it}\, S_{it})^2 + \sum_{j=1}^{16} \theta_j\, B_{ijt} + \mu_i + \lambda_t + \varepsilon_{it}\,.$$

Here:

- V_{it}^{H2} is the H2 volatility for firm i at time t,

- T_{it} is the regional temperature anomaly,
- S_{it} denotes the local sensitivity of heat extremes,
- $T_{it}\, S_{it}$ is the linear interaction capturing how local sensitivity modifies the effect of temperature anomalies,
- $(T_{it}\, S_{it})^2$ is the quadratic interaction accounting for nonlinear effects,
- B_{ijt} (for $j = 1, \ldots, 16$) are the Barra factor controls,
- μ_i represents firm fixed effects,
- λ_t captures time fixed effects, and
- ε_{it} is the error term.

Additional model forms, along with their results can be found in the supplementary material.

For the impact assessment, we are interested in calculating the effect of warming on equity returns over the sample period. To do so, we disentangle the warming signal from natural variability by detrending the temperature anomaly time series. This detrending procedure permits us to isolate changes attributable to systematic warming from those due to stochastic, natural fluctuations.

After detrending the anomalies through time, we calculate separately the effects attributable to natural variability and to systematic warming. In the results section, we focus solely on the warming component in order to isolate the impact of regional warming on equity returns. By doing so, we can quantify the extent to which increasing heat extremes, over and above natural temperature fluctuations, have materially affected firm-level returns over the sample period.

Acknowledgments

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1 Supplementary Material

Variable	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
Volatility	2.3854	1.4637	0.5860	1.4346	2.0075	2.8912	39.0366
Extreme Heat Probability	0.6692	0.7798	-1.9104	0.1143	0.6642	1.2278	4.6772
Beta	0.2144	1.0097	-2.5453	-0.5080	0.1008	0.8333	3.0137
Residual Volatility	-0.2216	0.9676	-2.8290	-0.9083	-0.4193	0.2609	3.0893
Liquidity	0.0973	0.9680	-3.0767	-0.4583	0.1418	0.6986	3.8255
Earnings Variability	0.3246	0.9816	-2.1137	-0.4180	0.0413	0.8253	4.8483
Momentum	-0.1437	0.9026	-3.4437	-0.5986	-0.0818	0.3903	2.9167
Book to Price	0.5224	0.9088	-2.1020	-0.1457	0.3972	1.0323	3.5423
Earnings Yield	-0.1631	0.9434	-3.4870	-0.5773	-0.0602	0.3490	3.5223
Dividend Yield	0.0215	1.0713	-1.8397	-0.9637	-0.1972	0.7323	3.4143
Long Term Reversal	0.0561	0.8836	-3.1067	-0.4429	0.0000	0.4757	3.2810
Profitability	-0.4233	1.0813	-3.9873	-1.3340	-0.6048	0.2243	3.8980
Earnings Quality	0.0047	0.9841	-3.4663	-0.6883	-0.0837	0.5553	4.1030
Investment Quality	-0.2387	1.0106	-3.9717	-0.7043	-0.0287	0.3916	3.8490
Leverage	0.0585	0.9982	-2.1443	-0.7483	-0.0743	0.6499	3.3833
Size	-2.1061	1.0777	-5.0733	-2.9043	-2.2043	-1.4250	1.1220
Mid Capitalization	-0.5080	1.3513	-2.7500	-1.8715	0.0022	0.7123	1.0413
Growth	-0.1412	0.9211	-3.7733	-0.6723	-0.2080	0.3169	3.5753

Table 1: Summary Statistics of Factor Exposures

Table 2: Impact of Heat Exposure on Log Vol H2

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Probability Quintile 1					-0.029^{**}	
					(0.013)	
Extreme Heat Probability Quintile 3					0.017	
					(0.011)	
Extreme Heat Probability Quintile 4					-0.007	
					(0.012)	
Extreme Heat Probability Quintile 5					0.026^{**}	
					(0.012)	
Extreme Heat Probability		0.007^{**}	0.007^{**}			
		(0.003)	(0.003)			
Extreme Heat Probability^2			-0.001			
			(0.002)			
Regional Anomaly	0.006^{*}			0.006^{*}		0.007^{**}
	(0.003)			(0.003)		(0.003)
Regional Anomaly * Sensitivity	0.003					0.002
	(0.002)					(0.002)
Sensitivity						0.002
						(0.002)
Entity FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Barra Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.402	0.401	0.401	0.401	0.402	0.740
Observations	12460	12460	12460	12460	12460	12534

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 3: Impact of Heat Exposure on Log Vol Summer

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Probability Quintile 1					-0.009	
					(0.012)	
Extreme Heat Probability Quintile 3					0.029^{***}	
					(0.010)	
Extreme Heat Probability Quintile 4					-0.002	
					(0.012)	
Extreme Heat Probability Quintile 5					0.035^{***}	
					(0.011)	
Extreme Heat Probability		0.006^{*}	0.006^{*}			
		(0.003)	(0.003)			
Extreme Heat Probability^2			0.001			
			(0.002)			
Regional Anomaly	0.005^{*}			0.005		0.006^{**}
	(0.003)			(0.003)		(0.003)
Regional Anomaly * Sensitivity	0.002					0.002
	(0.002)					(0.002)
Sensitivity						0.003^{*}
						(0.002)
Entity FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Barra Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.543	0.543	0.543	0.543	0.544	0.785
Observations	12460	12460	12460	12460	12460	12534

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Impact of Heat Exposure on Log Vol Q3

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Probability Quintile 1					-0.025^{*}	
					(0.013)	
Extreme Heat Probability Quintile 3					0.009	
					(0.011)	
Extreme Heat Probability Quintile 4					-0.010	
					(0.013)	
Extreme Heat Probability Quintile 5					0.014	
					(0.012)	
Extreme Heat Probability		0.006^{*}	0.006^{*}			
		(0.004)	(0.004)			
Extreme Heat Probability^2			0.000			
			(0.002)			
Regional Anomaly	0.005			0.004		0.006
	(0.003)			(0.003)		(0.003)
Regional Anomaly * Sensitivity	0.003^{*}					0.003
	(0.002)					(0.002)
Sensitivity						0.001
						(0.002)
Entity FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Barra Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.442	0.441	0.441	0.441	0.442	0.735
Observations	12460	12460	12460	12460	12460	12534

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 5: Impact of Heat Exposure on Log Vol Q4

	(1)	(2)	(3)	(4)	(5)	(6)
Extreme Heat Probability Quintile 1					-0.036^{**}	
					(0.016)	
Extreme Heat Probability Quintile 3					0.016	
					(0.015)	
Extreme Heat Probability Quintile 4					-0.017	
					(0.015)	
Extreme Heat Probability Quintile 5					0.027^{*}	
					(0.015)	
Extreme Heat Probability		0.006	0.007^{*}			
		(0.004)	(0.004)			
Extreme Heat Probability^2			-0.002			
			(0.002)			
Regional Anomaly	0.006			0.006		0.007^{*}
	(0.004)			(0.004)		(0.004)
Regional Anomaly * Sensitivity	0.002					0.002
	(0.002)					(0.002)
Sensitivity						0.003
						(0.002)
Entity FE	Yes	Yes	Yes	Yes	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Barra Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.253	0.253	0.253	0.253	0.254	0.637
Observations	12459	12459	12459	12459	12459	12533

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$