

Pricing Physical Climate Risk: Acute and Chronic Exposure

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Abstract

This paper examines whether equity markets incorporate acute and chronic physical climate exposure differently. I construct firm-level climate-risk measures by mapping county-level hazards to the geographic distribution of establishments and aggregating exposure using establishment sales and employment weights. The sample contains 505,255 firm-month observations for 4,452 U.S. public firms from 1990 to 2022. Firms with greater chronic exposure earn higher subsequent returns across portfolio sorts and cross-sectional regressions, whereas acute exposure has weaker and less stable predictive power. Climate-beta tests do not show that covariance with climate-mimicking portfolios commands a premium. Chronic-risk predictability is instead stronger among small firms, where investor attention and information processing are more limited. The evidence is therefore more consistent with gradual incorporation of persistent climate information than with compensation for systematic climate risk.

Keywords: Physical climate risk; chronic exposure; acute exposure; asset pricing; investor underreaction; information frictions

JEL Classification: G11; G12; G14; Q54

Job Market Paper

1 Introduction

Climate change has emerged as one of the most important long-term risks facing financial markets. Rising temperatures, increasing frequency of extreme weather events, prolonged droughts, and sea-level rise can affect firms through disruptions to operations, supply chains, productivity, and asset values. As these physical impacts intensify, understanding whether and how climate risks are incorporated into asset prices has become a central question in asset pricing and sustainable finance.

Existing literature generally distinguishes between transition risk and physical climate risk. Transition risk arises from policy changes, regulation, technological shifts, and evolving preferences associated with the transition toward a low-carbon economy. Physical climate risk, by contrast, reflects direct exposure to climate-related hazards and long-term environmental changes. Both channels may influence expected cash flows and discount rates and therefore affect firm valuation ([Hong et al., 2019](#); [Pankratz et al., 2023](#); [Addoum et al., 2020](#)).

A growing body of research documents that climate-related risks increasingly affect financial markets. Previous studies show that climate exposure can influence stock returns, operating performance, and investment behavior. However, evidence on whether physical climate risk commands a persistent premium remains mixed. One reason may be that existing measures often treat physical climate risk as a homogeneous concept, overlooking substantial heterogeneity across different forms of climate exposure.

Following the framework proposed by the Task Force on Climate-related Financial Disclosures (TCFD), physical climate risk can be separated into acute and chronic dimensions. Acute climate risk captures short-term, event-driven shocks such as hurricanes, floods, and wildfires. Chronic climate risk reflects persistent changes in environmental conditions, including sustained increases in temperature, drought exposure, humidity, and sea-level rise. These two forms of risk differ fundamentally in persistence, predictability, salience, and firms' ability to adapt.

This distinction is economically important. Acute climate shocks are typically sudden, highly visible, and localized. Because their effects are observable and often partially mitigated through insurance or diversification, investors may rapidly incorporate such information into prices. In contrast, chronic climate risks evolve gradually over long horizons and may require costly adaptation decisions, including relocation, supply-chain restructuring, or changes in production strategies. The slow-moving nature of chronic exposure makes its economic consequences more difficult to evaluate in real time.

Consequently, chronic climate risk may be particularly susceptible to delayed information

incorporation. This intuition relates closely to long-run risk frameworks ([Bansal et al., 2016](#)) and theories emphasizing limited attention and information frictions in financial markets. If investors respond slowly to persistent climate exposure, chronic risk may generate predictable return patterns without necessarily representing a conventionally priced systematic factor.

Motivated by these considerations, this paper asks a central question:

Do financial markets price short-term climate shocks and long-term climate exposure differently?

To address this question, I construct firm-level measures of acute and chronic climate risk using establishment-level geographic exposure aggregated with both sales and employment weights. Unlike headquarters-based approaches, establishment-level measures capture firms' distributed operational footprints and therefore provide a more comprehensive assessment of climate vulnerability. The analysis combines climate data from PRISM, NOAA, NIDIS, and SHELDUS with establishment-level information and CRSP–Compustat data to construct monthly firm-level climate exposure measures for U.S. publicly traded firms from 1990 to 2022.

The empirical analysis produces three main findings.

First, chronic climate risk strongly predicts future stock returns, whereas acute climate risk exhibits weak and unstable predictive power. Portfolio sorting results show that firms with higher chronic exposure consistently earn higher subsequent returns across multiple holding horizons. These return differentials remain significant after controlling for conventional asset pricing factors and mispricing-related factors.

Second, cross-sectional regressions confirm that chronic climate exposure remains positively associated with expected returns after controlling for standard firm characteristics, while acute climate exposure becomes economically small and statistically insignificant. The predictive power of chronic climate risk appears persistent across specifications.

Third, despite strong return predictability, climate beta tests provide little evidence that either acute or chronic climate exposure commands a significant systematic risk premium. Firm-level exposure to climate-mimicking factors does not significantly explain expected returns. This discrepancy suggests that the return predictability associated with chronic climate exposure is unlikely to arise solely from compensation for systematic covariance risk. Taken together, these findings point toward an interpretation based on slow information incorporation rather than conventional risk pricing. Chronic climate risk appears to behave less like a priced systematic factor and more like a persistent informational characteristic that investors gradually incorporate into valuations over time. By contrast, acute climate shocks appear more observable and rapidly reflected in prices, limiting their ability to generate

persistent return predictability.

This paper contributes to the literature in several ways.

First, it provides new evidence that physical climate risk is not uniformly priced, and that the pricing effects are concentrated primarily in chronic rather than acute exposure. This highlights the importance of distinguishing between persistent and transitory forms of climate risk.

Second, the paper contributes to the emerging literature on climate finance by introducing firm-level physical climate risk measures constructed from establishment-level exposure, allowing for a more comprehensive representation of firms' geographic operations than headquarters-based measures.

Third, the findings challenge standard asset pricing interpretations by showing that return predictability associated with chronic climate exposure persists despite weak evidence of climate beta pricing, suggesting an important role for information frictions and investor attention.

Finally, the results provide evidence that long-term climate exposure may generate market inefficiencies through delayed incorporation of slowly evolving risks, offering a behavioral perspective on how physical climate risk enters asset prices.

The remainder of the paper proceeds as follows. Section 2 describes the data sources and construction of acute and chronic climate risk measures. Section 3 presents empirical results, including portfolio sorts, cross-sectional regressions, and climate beta tests. Section 4 discusses interpretation and implications. Section 5 concludes.

2 Data and Methodology

2.1 Sample Construction

This study examines whether and how physical climate risk is incorporated into equity prices using a comprehensive panel of U.S. publicly listed firms. The baseline sample period is 1990–2022. Firm-level stock return data are obtained from the Center for Research in Security Prices (CRSP), while accounting variables are sourced from Compustat and merged through the CRSP–Compustat Merged (CCM) database.

Monthly stock returns are used to construct excess returns relative to the one-month Treasury bill rate. Standard firm characteristics commonly employed in asset pricing studies are included as control variables, including firm size, market-to-book ratio, profitability, asset growth, momentum, short-term reversal, return skewness, and idiosyncratic volatility. All

explanatory variables are lagged by one month to mitigate potential simultaneity concerns. The sample includes all common stocks listed on the NYSE, AMEX, and NASDAQ exchanges. To measure firms’ exposure to physical climate risk, firm-level financial information is linked with establishment-level geographic data. Unlike approaches relying solely on headquarters location, establishment-level exposure captures firms’ operational footprint across multiple geographic regions, thereby providing a more comprehensive measure of climate vulnerability.

The final analysis sample contains 505,255 firm-month observations covering 4,452 U.S. publicly listed firms from 1990 to 2022, providing substantial cross-sectional and time-series variation for identifying the pricing effects of climate exposure.

2.2 Construction of Physical Climate Risk Measures

Following the classification proposed by the Task Force on Climate-related Financial Disclosures (TCFD), physical climate risk is separated into **acute** and **chronic** dimensions. Acute climate risk captures short-term, event-driven shocks such as natural disasters, whereas chronic climate risk reflects long-run changes in climatic conditions that evolve gradually over time.

This distinction is economically meaningful because acute and chronic climate risks differ substantially in persistence, predictability, and firms’ ability to adapt. Acute shocks are often sudden and highly visible, while chronic exposure accumulates gradually and may require long-term operational adjustments.

2.2.1 Chronic Climate Risk

Chronic climate risk is constructed using county-level measures that capture persistent changes in climatic conditions over time. Specifically, the measure incorporates six dimensions of long-run climate exposure: extreme heat, extreme cold, humidity, precipitation, drought, and sea-level rise. Extreme weather variables are primarily derived from PRISM climate data and NOAA datasets, while drought exposure is measured using the Palmer Drought Severity Index (PDSI) obtained from NOAA and NIDIS. Sea-level rise exposure is constructed using inundation scenarios from NOAA’s Sea Level Rise Viewer.

Extreme climate indicators are defined relative to historical distributions. For example, extreme heat exposure is measured as the annual number of days with maximum temperatures exceeding the historical 90th percentile, whereas extreme cold exposure is defined as the annual number of days with minimum temperatures below the historical 10th percentile. Simi-

lar percentile-based thresholds are applied to humidity and precipitation measures. Drought exposure is captured using low PDSI conditions, while sea-level rise exposure is measured as the average inundation across multiple NOAA sea-level rise scenarios. Together, these variables capture persistent and cumulative climate conditions that may affect firms through gradual operational disruption, changes in productivity, and long-term adaptation costs. Definitions and data sources for all chronic climate risk components are summarized in [Table 1](#).

2.2.2 Acute Climate Risk

Acute climate risk captures realized short-term disaster exposure using county-year fatalities, nonfatal injuries, and disaster-event frequency from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). Each input is transformed using $\log(1 + x)$ before standardization. Fatalities capture the most severe realized human loss, injuries capture broader nonfatal harm, and event frequency measures repeated disruption without mechanically assigning greater exposure to wealthier counties through property values.

In contrast to chronic climate risk, which reflects gradual and persistent changes in environmental conditions, acute climate risk represents sudden and event-driven disruptions arising from extreme weather events. Such shocks may generate substantial short-term operational and financial impacts but are often more localized and transitory in nature.

Definitions and data sources for all acute climate risk variables are summarized in [Table 1](#).

[[Table 1 about here](#)]
Subcomponent Definitions

2.3 County-Level Climate Risk Index Construction

To construct composite measures of climate exposure, all underlying climate variables are standardized prior to dimensional reduction. Standardization ensures comparability across indicators measured on different scales and prevents a component from dominating merely because of its units.

Principal component analysis (PCA) is then performed separately for chronic and acute climate variables. PCA is useful because the inputs are correlated manifestations of broader physical exposure. Including them separately would create multicollinearity and would not yield a single measure that can be mapped consistently from counties to establishments and firms, while equal weighting would impose identical contributions by assumption. PCA in-

stead derives weights from the covariance structure and summarizes shared variation without repeatedly counting highly correlated indicators (Jolliffe and Cadima, 2016). Estimating the two PCAs separately preserves the conceptual distinction between persistent climate conditions and realized disaster shocks.

The first principal component is retained as the composite climate risk measure for each category:

Chronic risk:

$$Risk_{county,t}^{chronic} = PC1(Chronic)$$

Acute risk:

$$Risk_{county,t}^{acute} = PC1(Acute)$$

PC1 is retained because it is the single linear combination that captures the largest possible share of standardized variation and therefore supplies a parsimonious, ex ante rule for extracting the dominant common exposure signal. Later components contain orthogonal residual contrasts that do not necessarily have a common “more climate risk” interpretation. PC1 is consequently a summary of dominant common variation, not a complete measure of every hazard or an estimate of each component’s causal importance. The chronic PC1 explains 38.83% of standardized variation, while the acute PC1 explains 42.31%. [Appendix Table A1](#) reports the component loadings and explained-variance shares. Higher index values are oriented to indicate greater exposure.

2.4 Mapping Climate Risk to Establishments

County-level climate risk measures are linked to firm establishments using geographic identifiers (county FIPS codes). Each establishment inherits the climate risk associated with its geographic location:

$$Risk_{establishment} = Risk_{county}.$$

This approach captures heterogeneous exposure across firms’ operational networks and allows firms with geographically diversified establishments to exhibit different climate profiles.

2.5 Aggregation to Firm-Level Climate Exposure

Establishment-level climate exposures are aggregated to the firm level using both sales-based and employment-based weights. Specifically, firm-level climate exposure is calculated as:

Sales-weighted exposure:

$$Risk_{i,t}^{sales} = \sum_j w_{ij}^{sales} Risk_{j,t}$$

Employment-weighted exposure:

$$Risk_{i,t}^{emp} = \sum_j w_{ij}^{emp} Risk_{j,t}$$

where w_{ij} denotes establishment-level weights based on either sales or employment shares. This aggregation approach differs from headquarters-based measures because it reflects firms' distributed operational exposure to climate risk.

The complete construction process is summarized in [Figure 1](#).

[[Figure 1](#) about here]

Construction of Firm-Level Climate Risk Measures

2.6 Variable Definitions and Summary Statistics

[Table 2](#) defines the main variables used in the empirical analysis, and [Table 3](#) reports the corresponding summary statistics. The sample contains broad cross-sectional dispersion in firm characteristics and climate exposure. Chronic climate risk displays substantially greater variation than acute climate risk, consistent with the idea that long-run physical exposure differs persistently across firms' operating footprints.

Control variables generally align with prior asset pricing studies. For example, the average firm size is comparable to large-cap publicly traded firms, while momentum and idiosyncratic volatility exhibit substantial cross-sectional variation.

All continuous variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers. Momentum, short-term reversal, skewness, and idiosyncratic volatility are measured using lagged return information so that the empirical specifications use information available before portfolio formation or return realization.

Variable definitions are listed in [Table 2](#). Summary statistics are reported in [Table 3](#).

[Table 2 about here]

Variable Definitions

[Table 3 about here]

Summary Statistics

3 Results

3.1 Portfolio Evidence on Climate Risk Pricing

To examine whether climate exposure predicts future returns, firms are sorted annually into tercile portfolios based on lagged climate risk measures. Portfolio returns are value-weighted using lagged market capitalization and reported at the 6-, 12-, and 18-month horizons, which capture the medium- and longer-horizon pricing pattern most relevant to the chapter’s delayed-incorporation interpretation. Risk-adjusted alphas are estimated using several benchmark models. The Fama–French five-factor model (FF5) includes the market, size, value, profitability, and investment factors of [Fama and French \(2015\)](#). The q-factor model includes the market, size, investment, and profitability factors proposed by [Hou, Xue, and Zhang \(2015\)](#). The mispricing-factor specification uses the management and performance mispricing factors of [Stambaugh and Yuan \(2017\)](#), and the FF5+Mis specification augments FF5 with those mispricing factors. These specifications separate compensation for standard risk factors from return patterns that are more closely related to anomaly-based mispricing. For portfolio p , horizon h , and benchmark model m , risk-adjusted performance is estimated from

$$R_t^{p,h} - R_{f,t} = \alpha_m^{p,h} + b_m^{p,h'} F_t^m + \varepsilon_t^{p,h}, \quad (1)$$

where F_t^m contains the factors in FF5, q, Mis, or FF5+Mis. The reported High–Low alpha is the intercept for the return difference between the high- and low-climate-risk portfolios. Returns and alphas are expressed as monthly percentages.

3.1.1 Acute Climate Risk

Panel A of [Table 4](#) shows that firms with higher acute climate risk generally earn higher future returns than firms with lower exposure. The High–Low portfolio spread becomes economically meaningful at longer holding horizons, reaching 0.086% and 0.075% per month at the 12-month and 18-month horizons, respectively. Under the FF5 specification, corresponding alpha spreads remain positive and statistically significant.

[Table 4 about here]

Climate Risk-Sorted Portfolio Returns and Risk-Adjusted Alphas Across Short- and Long-Horizon Holding Periods

However, the predictive power of acute climate risk weakens substantially after controlling for mispricing-related factors. Under FF5+Mis and the mispricing-factor model, most abnormal return spreads become statistically insignificant. This attenuation suggests that acute climate risk overlaps with known anomaly-related characteristics and is unlikely to represent an independent source of systematic risk. Instead, the observed predictability may reflect temporary investor mispricing associated with highly visible climate shocks.

Overall, while acute climate exposure exhibits some predictive power, the evidence is weak and unstable across specifications.

3.1.2 Chronic Climate Risk

The results for chronic climate risk are substantially stronger and more persistent. Across the reported 6-, 12-, and 18-month horizons, portfolios with higher chronic climate exposure consistently outperform portfolios with lower exposure in both raw returns and risk-adjusted alphas. For example, at the 18-month horizon, the High–Low portfolio generates abnormal returns exceeding 0.20% per month after controlling for mispricing factors. Importantly, these effects remain statistically significant across all asset pricing models considered.

Unlike acute climate risk, chronic climate exposure continues to predict future returns even after accounting for conventional risk factors and known anomalies. This persistence suggests that chronic climate risk captures an economically meaningful dimension of exposure not fully reflected in existing asset pricing models.

3.1.3 Cumulative Portfolio Performance

Figure 2 further illustrates this pattern by plotting cumulative returns of High–Low climate risk portfolios. The cumulative performance of chronic climate risk portfolios diverges steadily over time and exceeds that of acute risk portfolios, indicating stronger long-term return predictability associated with persistent climate exposure.

[Figure 2 about here]

Cumulative Returns of High-minus-Low Climate Risk Portfolios

Taken together, the portfolio evidence suggests that chronic climate risk is priced more strongly and persistently than acute climate risk.

3.2 Cross-Sectional Predictability: Fama–MacBeth Regressions

The monthly cross-sectional regression is

$$R_{i,t}^e = a_t + \beta_t \text{ClimateRisk}_{i,t-1} + \gamma_t' Z_{i,t-1} + \delta_{s,t} + \varepsilon_{i,t}, \quad (2)$$

where $R_{i,t}^e$ is the monthly excess return, $Z_{i,t-1}$ contains size, market-to-book ratio, asset growth, ROA, momentum, reversal, return skewness, and idiosyncratic volatility, and $\delta_{s,t}$ denotes industry effects in each monthly cross-section. The table reports time-series averages of the monthly slope estimates. Inference uses kernel-adjusted standard errors for the coefficient series.

Table 5 presents Fama–MacBeth regressions examining the relationship between lagged climate risk exposure and future excess returns while controlling for standard firm characteristics. The results show that chronic climate risk remains positively associated with future returns across specifications and retains statistical significance after including controls for size, market-to-book ratio, profitability, momentum, short-term reversal, skewness, and idiosyncratic volatility.

[Table 5 about here]

Return Predictive Power of Climate Risks: Fama–MacBeth Regressions

In contrast, coefficients on acute climate risk are small and generally insignificant once firm characteristics are included. This finding reinforces the portfolio evidence and suggests that acute climate exposure does not represent a stable predictor of expected returns.

Importantly, the significance of chronic climate risk remains robust after including industry fixed effects, indicating that the observed pricing effects are not solely driven by sectoral composition. The results therefore support the interpretation that chronic climate exposure contributes incremental information beyond traditional predictors of expected returns.

Overall, Fama–MacBeth regressions confirm that long-term climate exposure is associated with persistent cross-sectional return differences.

3.3 Is Climate Risk a Priced Systematic Factor? Evidence from Climate Beta Tests

To examine whether physical climate risk represents a priced systematic factor, climate-mimicking portfolios are constructed and firm-level climate betas are estimated using rolling 36-month regressions. Climate factors are defined as monthly High–Low portfolio returns

sorted on lagged climate exposure, and firm-specific climate betas measure covariance with these climate factors over time.

The first-stage rolling time-series regression is

$$R_{i,\tau}^e = a_i + \beta_{i,t}^{Climate} F_{\tau}^{Climate} + u_{i,\tau}, \quad \tau = t - 35, \dots, t, \quad (3)$$

where $F_{\tau}^{Climate}$ is the acute or chronic High–Low climate-mimicking return. The estimated climate beta is then entered into the monthly pricing regression

$$R_{i,t+1}^e = a_t + \lambda_t \hat{\beta}_{i,t}^{Climate} + \gamma_t' Z_{i,t} + \varepsilon_{i,t+1}. \quad (4)$$

The controls $Z_{i,t}$ are firm size, momentum, short-term reversal, skewness, and idiosyncratic volatility. Table 6 reports the time-series mean of λ_t from the Fama–MacBeth second stage. Table 6 reports Fama–MacBeth regressions testing whether exposure to systematic climate shocks commands a risk premium. The results indicate that neither chronic nor acute climate beta exhibits statistically significant explanatory power for future returns. The coefficient on chronic climate beta is negative but economically small (-0.0457, $t = -0.87$), while the coefficient on acute climate beta is similarly insignificant (-0.0360, $t = -0.65$).

[Table 6 about here]
Climate Beta Pricing Tests

These findings stand in contrast to earlier results showing that chronic climate exposure characteristics significantly predict future returns. The discrepancy suggests that the return predictability associated with chronic climate exposure is unlikely to arise from compensation for systematic covariance risk, as implied by standard asset pricing theory.

Instead, the evidence is more consistent with slow information diffusion or delayed incorporation of long-term climate exposure into prices. Chronic climate risks—including persistent warming, drought exposure, and sea-level rise—evolve gradually and may be difficult for investors to evaluate in real time. Consequently, prices may adjust only slowly, generating persistent return predictability without requiring climate risk to be a conventionally priced systematic factor.

By contrast, acute climate shocks tend to be highly observable and more rapidly incorporated into prices, which may explain their weaker predictive power. Overall, the evidence favors an interpretation based on incomplete information incorporation rather than equilibrium risk compensation.

3.4 Information Frictions and Low-Attention Firms

To examine the information-friction mechanism more directly, I test whether climate-risk return predictability is stronger among firms with lower investor attention. I use small firms as the main proxy for low attention and limited information processing. Each month, firms are sorted into size terciles, and the small-firm indicator equals one for firms in the bottom tercile of market capitalization. I then estimate monthly Fama–MacBeth regressions of future excess returns on climate exposure, the small-firm indicator, and their interaction, controlling for standard firm characteristics.

For each return horizon $h \in \{6, 12, 18\}$ months, the monthly cross-sectional model is

$$R_{i,t+h}^e = a_t + \beta_t \text{ClimateRisk}_{i,t-1} + \eta_t \text{Small}_{i,t-1} + \phi_t (\text{ClimateRisk}_{i,t-1} \times \text{Small}_{i,t-1}) + \gamma_t' Z_{i,t-1} + \varepsilon_{i,t+h}. \quad (5)$$

The coefficient β_t is the climate-risk slope among non-small firms, and ϕ_t is the incremental slope for small firms. The control vector includes size, market-to-book ratio, asset growth, profitability, momentum, reversal, skewness, and idiosyncratic volatility. Table 7 reports time-series averages of the monthly coefficients with Newey–West standard errors.

Table 7 reports the results. The interaction between chronic climate risk and the small-firm indicator is positive and statistically significant across all horizons. For sales-weighted chronic risk, the interaction coefficient is 0.0011% per month at the 6-month horizon ($t = 3.00$), 0.0008% at the 12-month horizon ($t = 2.61$), and 0.0008% at the 18-month horizon ($t = 2.69$). Employment-weighted chronic risk produces a similar pattern.

[\[Table 7 about here\]](#)

Information Frictions and Climate-Risk Pricing: Small-Firm Tests

The acute-risk placebo results are less persistent. Acute risk interactions are significant at the 6-month horizon but disappear at the 12- and 18-month horizons. This contrast is consistent with the interpretation that chronic climate exposure is a slow-moving information signal that investors incorporate gradually, especially among firms receiving less attention.

Additional diagnostics support this interpretation. In full-sample Fama–MacBeth regressions, chronic-risk coefficients are weak at the 1- to 6-month horizons but turn positive at the 12- and 18-month horizons. The climate-risk measures also differ sharply in persistence: the 12-month autocorrelation is approximately 0.88 for chronic risk but only about 0.04 for acute risk. These patterns strengthen the view that chronic physical risk behaves as persistent information that is only gradually incorporated into prices.

3.5 Discussion: Risk Premium or Information Friction?

Taken together, the empirical findings suggest a consistent pattern. First, chronic climate exposure predicts future returns in portfolio sorts and cross-sectional regressions. Second, climate beta tests provide little evidence that covariance exposure to climate shocks is priced. Third, the pricing effects are stronger among small firms, where investor attention and information processing are likely to be more limited.

This combination of results is difficult to reconcile with a standard risk-premium explanation alone. If chronic climate exposure represented compensation for systematic covariance risk, climate betas should help explain the cross-section of expected returns. Instead, the beta tests are insignificant, while characteristic-based exposure continues to matter in portfolio and subsample evidence.

Accordingly, chronic climate exposure appears to behave less like a conventionally priced systematic risk factor and more like a slow-moving informational characteristic. The evidence is consistent with gradual learning, limited investor attention, and incomplete incorporation of persistent physical climate exposure into asset prices.

4 Conclusion

This paper examines how equity markets respond to different dimensions of physical climate risk by distinguishing between acute and chronic climate exposure. Using firm-level climate risk measures constructed from establishment-level geographic exposure, the results reveal substantial heterogeneity in how climate risks are reflected in future stock returns.

The findings show that chronic climate risk is associated with persistent return predictability across portfolio sorts, cross-sectional regressions, and several heterogeneity tests, whereas acute climate risk exhibits weaker and less stable predictive power. Climate beta tests indicate that neither acute nor chronic climate systematic risk commands a significant risk premium. Together, these results suggest that the return predictability linked to chronic climate exposure is unlikely to reflect compensation for bearing systematic climate covariance risk.

Instead, the evidence is more consistent with incomplete incorporation of long-term climate information, investor underreaction, and persistent information frictions. The strongest chronic-exposure effects appear among smaller firms, where investor attention and information processing are likely to be more limited. These findings highlight the importance of distinguishing acute from chronic physical climate risk and of improving disclosure around

firms' distributed operational exposure.

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Tables and Figures

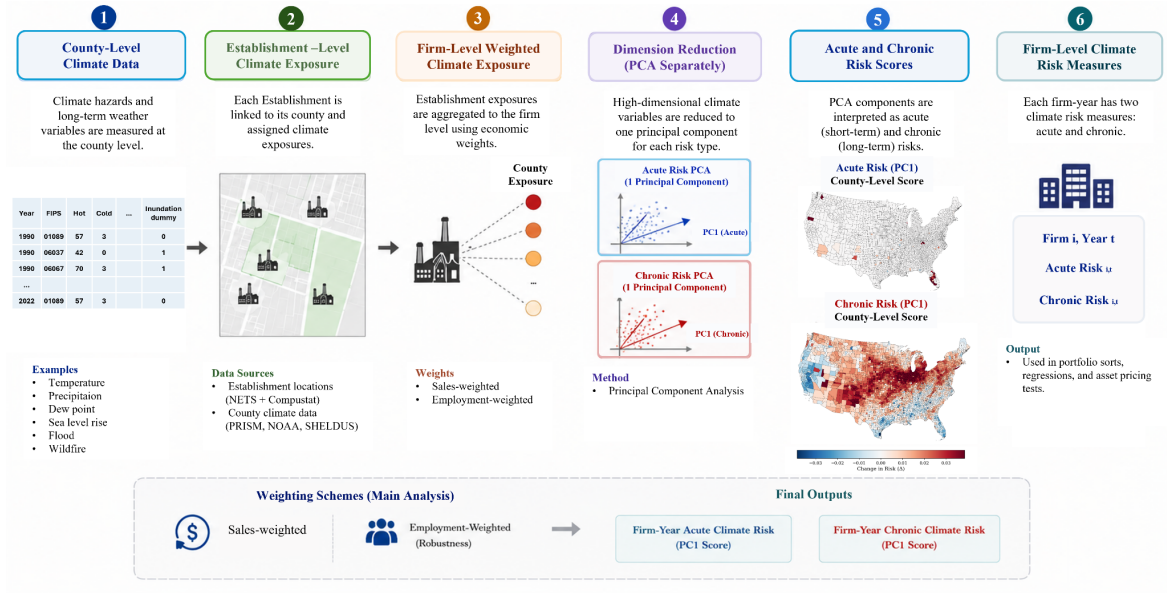


Figure 1. Construction of Firm-Level Climate Risk Measures

Notes: County-level climate components are standardized and summarized separately into chronic and acute PC1 indices. County exposure is assigned to establishments through county FIPS identifiers and then aggregated to the firm-year level using establishment sales or employment shares.

(1) Type	(2) Component	(3) Source	(4) Definition
Chronic Risk	Extreme Heat Days	PRISM	Annual days with max-temperature above the 90th percentile (P90).
	Extreme Cold Days	PRISM	Annual days with min-temperature below the 10th percentile (P10).
	Extreme Humidity Days	PRISM	Annual days with dew point above the 90th percentile (P90).
	Extreme Wet Days	PRISM	Annual days with precipitation above the 90th percentile (P90).
	Extreme Dry Days	NOAA & NIDIS	Annual days with PDSI below the 10th percentile (P10)
Acute Risk	Sea Level Rise Exposure	NOAA	Average inundation exposure across NOAA sea-level-rise scenarios (1–6 ft).
	Fatalities	SHELDUS	Log of one plus disaster-related deaths from climate events.
	Injuries	SHELDUS	Log of one plus nonfatal injuries from climate events.
	Event Frequency	SHELDUS	Log of one plus the number of disaster-event records.

Table 1. Subcomponent Definitions

Notes: Table 1 presents the subcomponents used to construct the physical climate risk measures.

	(1) Description
Dependent Variable	
Excess Return	Monthly stock return in excess of the risk-free rate.
Climate Risk Measures	
Acute Risk (Sales)	Firm-level exposure to acute climate risk, aggregated across establishments using sales weights, lagged by one month.
Acute Risk (Employment)	Firm-level exposure to acute climate risk, aggregated using employment weights, lagged by one month.
Chronic Risk (Sales)	Firm-level exposure to chronic climate risk, aggregated using sales weights, lagged by one month.
Chronic Risk (Employment)	Firm-level exposure to chronic climate risk, aggregated using employment weights, lagged by one month.
Firm Characteristics	
Log Size	Natural logarithm of market equity.
Market-to-Book	Ratio of market equity to book equity.
Asset Growth	Annual growth rate of total assets.
Profitability	Return on assets, defined as net income divided by total assets.
Return-Based Predictors	
Momentum	Cumulative stock return over months t-12 to t-2.
Short-Term Reversal	Stock return in month t-1.
Return Skewness	Skewness of stock returns over the past 12 months.
Idiosyncratic Volatility	Standard deviation of residuals from a Fama-French five-factor model estimated over a rolling 12-month window.

Table 2. Variable Definitions

(1) Variable	(2) N	(3) Firms	(4) Mean	(5) Std. Dev.	(6) P25	(7) Median	(8) P75	(9) P99
Excess return $_{i,t}$	505,255	4,452	-0.002	0.002	-0.004	-0.002	0.000	0.004
Size $_{i,t-1}$	505,255	4,452	13.018	2.168	11.411	12.964	14.528	18.283
M/B ratio $_{i,t-1}$	505,255	4,452	3.114	4.513	1.105	1.759	3.155	33.274
Asset growth $_{i,t-1}$	505,255	4,452	0.150	0.387	-0.017	0.065	0.193	2.323
Profitability $_{i,t-1}$	505,255	4,452	-0.012	0.188	-0.004	0.023	0.066	0.281
Log assets $_{i,t-1}$	505,255	4,452	6.470	2.170	4.964	6.509	7.918	11.867
Momentum $_{i,t-1}$	505,255	4,452	1.937	8.207	-0.465	0.062	1.048	66.724
Reversal $_{i,t-1}$	505,255	4,452	0.011	0.134	-0.057	0.006	0.070	0.504
Ret. skewness $_{i,t-1}$	505,255	4,452	-0.047	3.248	-3.464	-0.071	3.464	3.464
Idio. vol. $_{i,t-1}$	505,255	4,452	0.001	0.001	0.001	0.001	0.001	0.004
Acute risk (Sales) $_{i,t-1}$	505,255	4,452	0.109	0.451	-0.023	-0.022	0.017	3.327
Acute risk (Emp.) $_{i,t-1}$	505,255	4,452	0.110	0.448	-0.023	-0.021	0.019	3.300
Chronic risk (Sales) $_{i,t-1}$	505,255	4,452	0.337	1.185	-0.084	0.352	0.873	3.648
Chronic risk (Emp.) $_{i,t-1}$	505,255	4,452	0.337	1.180	-0.086	0.351	0.873	3.621

Table 3. Summary Statistics

Notes: This table reports summary statistics for 505,255 firm-month observations covering 4,452 firms from 1990 to 2022. Excess returns are monthly excess returns. Climate risk measures are firm-level establishment-weighted exposures. All continuous variables are winsorized at the 1st and 99th percentiles.

Panel A. Acute Climate Risk (Employment-Weighted)

(1) Signal	(2) Horizon	(3) Portfolio	(4) Mean	(5) FF5	(6) FF5+Mis	(7) q	(8) Mis
Acute	6M	Low	0.881*** (8.443)	0.637*** (6.351)	0.657*** (5.600)	0.691*** (6.524)	0.645*** (5.431)
		Mid	0.920*** (9.063)	0.692*** (7.192)	0.747*** (6.744)	0.731*** (7.155)	0.729*** (6.413)
		High	0.983*** (11.194)	0.708*** (8.627)	0.675*** (7.228)	0.724*** (8.274)	0.668*** (7.051)
		H-L	0.102** (2.224)	0.071 (1.513)	0.018 (0.350)	0.032 (0.653)	0.023 (0.447)
	12M	Low	0.886*** (12.576)	0.693*** (9.599)	0.735*** (8.820)	0.728*** (9.496)	0.726*** (8.566)
		Mid	0.940*** (13.513)	0.762*** (11.079)	0.812*** (10.484)	0.786*** (10.669)	0.797*** (9.951)
		High	0.972*** (15.434)	0.763*** (12.083)	0.725*** (10.106)	0.778*** (11.586)	0.718*** (9.848)
		H-L	0.086*** (2.696)	0.070** (2.108)	-0.011 (-0.294)	0.051 (1.430)	-0.008 (-0.229)
	18M	Low	0.893*** (16.073)	0.690*** (11.573)	0.707*** (9.962)	0.688*** (10.832)	0.704*** (9.806)
		Mid	0.978*** (18.897)	0.779*** (14.612)	0.806*** (13.078)	0.775*** (13.555)	0.804*** (12.766)
		High	0.967*** (18.815)	0.745*** (13.844)	0.692*** (11.071)	0.734*** (12.830)	0.695*** (11.022)
		H-L	0.075*** (2.795)	0.055** (1.982)	-0.015 (-0.497)	0.046 (1.547)	-0.009 (-0.288)

Panel B. Chronic Climate Risk (Employment-Weighted)

(1) Signal	(2) Horizon	(3) Portfolio	(4) Mean	(5) FF5	(6) FF5+Mis	(7) q	(8) Mis
Chronic	6M	Low	0.838*** (8.869)	0.571*** (6.263)	0.582*** (5.394)	0.588*** (6.092)	0.576*** (5.317)
		Mid	1.011*** (11.317)	0.765*** (9.247)	0.740*** (8.067)	0.786*** (8.862)	0.726*** (7.658)
		High	0.979*** (9.152)	0.713*** (6.933)	0.774*** (6.380)	0.763*** (7.027)	0.766*** (6.264)
		H-L	0.140*** (3.456)	0.142*** (3.346)	0.192*** (3.960)	0.176*** (3.933)	0.189*** (3.901)
		Low	0.830*** (12.488)	0.626*** (9.222)	0.650*** (8.137)	0.629*** (8.728)	0.642*** (7.932)
	12M	Mid	1.005*** (15.725)	0.815*** (12.976)	0.779*** (11.252)	0.833*** (12.371)	0.768*** (10.716)
		High	0.993*** (13.812)	0.784*** (10.699)	0.851*** (10.044)	0.822*** (10.605)	0.845*** (9.889)
		H-L	0.163*** (5.466)	0.158*** (5.079)	0.200*** (5.890)	0.193*** (5.891)	0.203*** (5.991)
		Low	0.843*** (15.871)	0.635*** (11.275)	0.629*** (9.290)	0.613*** (10.252)	0.626*** (9.171)
	18M	Mid	0.998*** (19.519)	0.790*** (15.002)	0.742*** (12.421)	0.783*** (13.880)	0.743*** (12.197)
		High	1.019*** (18.912)	0.797*** (13.958)	0.832*** (12.301)	0.794*** (13.131)	0.832*** (12.266)
		H-L	0.176*** (7.558)	0.162*** (6.664)	0.203*** (8.106)	0.181*** (6.993)	0.206*** (8.189)

Table 4. Climate Risk-Sorted Portfolio Returns and Risk-Adjusted Alphas Across Short- and Long-Horizon Holding Periods

Notes: This table reports value-weighted monthly returns and risk-adjusted alphas for tercile portfolios sorted on lagged climate risk. H–L is the High-minus-Low portfolio. Returns and alphas are monthly percentages for 6-, 12-, and 18-month holding periods. FF5, FF5+Mis, q, and Mis denote the corresponding alpha models. t-statistics are in parentheses; *, **, and *** denote significance at the 10%, 5%, and 1% levels.

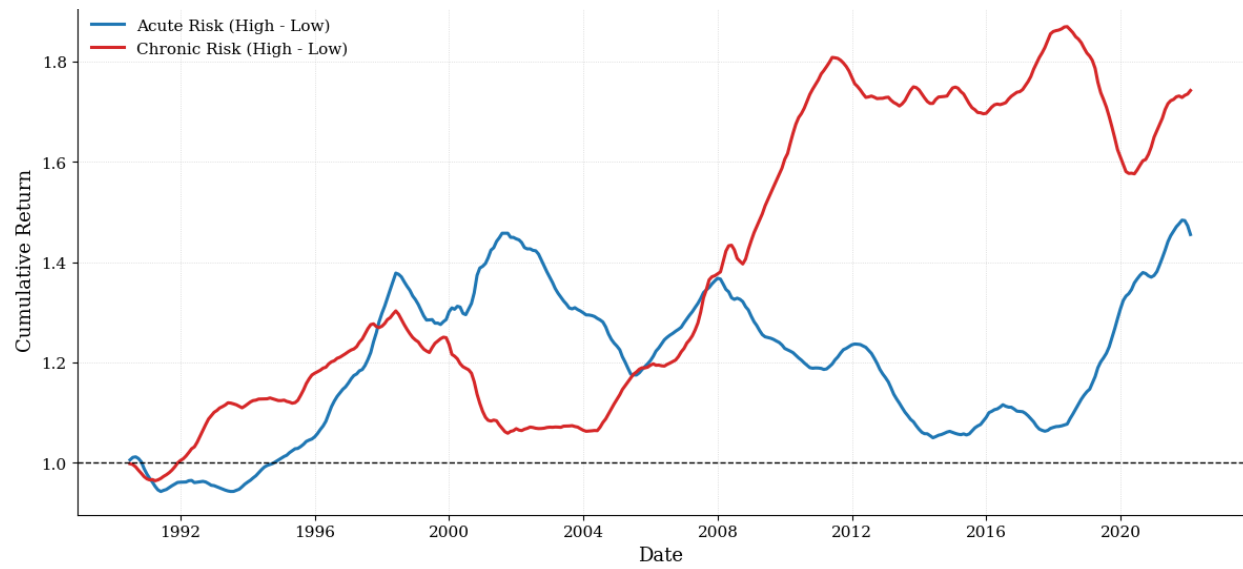


Figure 2. Cumulative Returns of High-minus-Low Climate Risk Portfolios
Notes: Firms are sorted into terciles based on lagged climate risk and cumulative H–L returns are plotted over time.

	(1)	(2)	(3)	(4)	(5)	(6)
			Excess ret. $_{i,t}$			
Acute risk (Sales) $_{i,t-1}$	0.0003 (0.21)	-0.0004 (-0.40)			0.0001 (0.05)	-0.0004 (-0.39)
Chronic risk (Sales) $_{i,t-1}$			0.0015*** (4.28)	0.0006** (2.02)	0.0015*** (4.31)	0.0006** (2.20)
Size $_{i,t-1}$		0.0025*** (9.26)		0.0025*** (9.29)		0.0025*** (9.27)
M/B ratio $_{i,t-1}$		-0.0165*** (-18.85)		-0.0165*** (-18.78)		-0.0165*** (-18.82)
Asset growth $_{i,t-1}$		0.0151*** (11.30)		0.0151*** (11.28)		0.0150*** (11.24)
ROA $_{i,t-1}$		0.0498*** (16.01)		0.0497*** (15.98)		0.0497*** (15.97)
Momentum $_{i,t-1}$		0.0010** (1.99)		0.0010** (1.99)		0.0010** (1.98)
Reversal $_{i,t-1}$		0.1023*** (7.47)		0.1023*** (7.46)		0.1023*** (7.47)
Ret. skewness $_{i,t-1}$		0.0020*** (7.05)		0.0020*** (7.08)		0.0020*** (7.08)
Idio. vol. $_{i,t-1}$		23.9366*** (10.26)		23.9782*** (10.26)		23.9542*** (10.26)
N (firms)	1312	1312	1312	1312	1312	1312
Adj. R ²	0.001	0.143	0.001	0.143	0.002	0.144
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Return Predictive Power of Climate Risks: Fama–MacBeth Regressions

Notes: This table reports Fama–MacBeth regressions of monthly excess returns on climate risk measures. All explanatory variables are lagged by one month. M/B ratio denotes market-to-book ratio; Reversal denotes short-term reversal; Ret. skewness denotes return skewness; Idio. vol. denotes idiosyncratic volatility. T-statistics based on kernel-adjusted standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Chronic Beta Test Excess return i,t	(2) Acute Beta Test Excess return i,t
Climate Beta (Chronic) $i,t-1$	-0.0457 (-0.87)	
Climate Beta (Acute) $i,t-1$		-0.0360 (-0.65)
Log Size $i,t-1$	-0.0569* (-1.72)	-0.0582* (-1.82)
Momentum $i,t-1$	0.8683*** (5.60)	0.8912*** (5.54)
Short-Term Reversal $i,t-1$	0.6414* (1.86)	0.7468** (2.11)
Skewness $i,t-1$	-0.0748** (-2.07)	-0.0813** (-2.18)
Idiosyncratic Volatility $i,t-1$	-4.4137*** (-2.59)	-4.7483*** (-2.91)
Constant	-16.4994*** (-4.68)	-16.5261*** (-4.94)
Observations	1,650,475	1,650,475
Adj. R ²	-0.0017	-0.0020
Number of Months	359	359

Table 6. Climate Beta Pricing Tests

Notes: This table reports Fama–MacBeth regressions testing whether systematic exposure to climate-related return shocks is associated with expected stock returns. Climate betas are estimated using rolling 36-month regressions on climate-mimicking portfolio returns constructed from lagged climate risk exposure. The dependent variable is monthly excess return. Control variables include firm size, momentum, short-term reversal, skewness, and idiosyncratic volatility. Number of Months is the number of monthly cross-sectional regressions entering the Fama–MacBeth second-stage average.

(1) Signal	(2) Horizon	(3) Small-firm int.	(4) t-stat	(5) Sig.	(6) Months
Chronic risk (Sales) $_{i,t-1}$	6M	0.0011	3.00	***	379
Chronic risk (Sales) $_{i,t-1}$	12M	0.0008	2.61	***	373
Chronic risk (Sales) $_{i,t-1}$	18M	0.0008	2.69	***	367
Chronic risk (Emp.) $_{i,t-1}$	6M	0.0010	2.71	***	379
Chronic risk (Emp.) $_{i,t-1}$	12M	0.0008	2.54	**	373
Chronic risk (Emp.) $_{i,t-1}$	18M	0.0008	2.69	***	367
Acute risk (Sales) $_{i,t-1}$	6M	0.0005	2.12	**	379
Acute risk (Sales) $_{i,t-1}$	12M	-0.0000	-0.15		373
Acute risk (Sales) $_{i,t-1}$	18M	0.0000	0.18		367
Acute risk (Emp.) $_{i,t-1}$	6M	0.0005	2.11	**	379
Acute risk (Emp.) $_{i,t-1}$	12M	-0.0000	-0.15		373
Acute risk (Emp.) $_{i,t-1}$	18M	0.0000	0.01		367

Table 7. Information Frictions and Climate-Risk Pricing: Small-Firm Tests

Notes: This table reports monthly Fama–MacBeth regressions of future excess returns on climate-risk exposure, a small-firm indicator, and their interaction. Small firms are firms in the bottom monthly tercile of market capitalization. The small-firm interaction reports the incremental climate-risk slope for small firms relative to other firms. All specifications control for size, market-to-book ratio, asset growth, profitability, momentum, reversal, skewness, and idiosyncratic volatility. Coefficients are monthly percentage points. t-statistics are based on Newey–West standard errors from the monthly coefficient series. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

Appendix

Index	(1) Heat	(2) Cold	(3) Humidity	(4) Dry	(5) Wet	(6) Sea level	(7) PC1 variance
Chronic risk	0.470	-0.531	0.595	0.033	0.326	0.187	0.388
Acute risk	0.313	0.676	0.667				0.423

Appendix Table A1. PCA Loadings and Explained Variance

Notes: County-year inputs are standardized before PCA. Acute inputs are transformed using $\log(1 + x)$. Component signs are oriented so larger index values represent greater exposure. The negative cold loading indicates that fewer extremely cold days align with the dominant chronic-exposure component. PCA loadings summarize covariance and are not estimates of separate causal effects.