When Storms Hit Markets:

A market-based approach to measuring acute storm impact on stocks

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Abstract

Physical climate risks pose significant challenges to financial markets. However, existing approaches to quantification often fail to capture the true economic impacts of extreme weather events.

This paper introduces a novel market-based methodology for quantifying acute storm risk, that leverages historical stock market responses to extreme weather events.

Our market-based framework captures the broad financial impacts of storm events that drive investor outcomes, including supply chain disruptions, demand shifts, competitive repositioning, and adaptation costs. These have far greater materiality than insured 'location-specific' losses, from direct physical damage at sites, which are the basis of traditional approaches.

Our methodology works for the vast majority of public companies. The models extract systematic 'storm sensitivity' patterns from observable market responses, rather than requiring granular geographic asset disclosures, that may not be available. This provides portfolio-wide coverage for institutional investors, offering material advantages for equity investors whose risk assessment needs to extend beyond site-specific physical exposure to portfolio-wide systematic vulnerability.

We develop empirical damage-to-performance models that capture actual market corrections rather than theoretical estimates. This is done by analyzing the post-event performance of companies across 37 storm-sensitive industries in the United States, from 2000 to 2024. Our analysis examines 45 major storm events, that caused at least $5 billion in damages. We focus on the 26-week post-event impact on publicly traded companies across multiple industries and sectors.

We identify statistically significant negative relationships between storm damages and stock returns across six industries (β: -0.05 to -0.17) including Homebuilding, Electric Utilities, Energy Infrastructure, and Insurance, and five sectors (β: -0.04 to -0.12) led by Agriculture and Real Estate Development.

The empirical foundation of our methodology enables forward-looking storm risk quantification that balances statistical rigor with comprehensive coverage, while maintaining compatibility with investment portfolio analysis needs.

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Executive Summary

Climate change poses substantial financial risks to companies across all sectors of the global economy. These risks manifest through physical channels (direct damage from extreme weather events) and transition pathways (policy, technology, and market shifts toward decarbonization). Financial markets, companies, and regulators, increasingly recognize the need to quantify these risks, to inform investment decisions, strategic planning, and disclosure practices.

This research introduces a market-based methodology for quantifying storm vulnerability that addresses a critical gap in existing climate risk assessment frameworks.

Traditional location-based approaches, which overlay company facilities with hazard maps to calculate physical asset exposure, remain important for insurance underwriting and site-specific risk evaluation.

However, they provide limited utility for investors managing diversified portfolios, because they cannot capture how storm events propagate through supply chains, affect customer demand, alter competitive dynamics, or interact with corporate risk management strategies.

More fundamentally, they cannot assess storm vulnerability for the vast majority of publicly traded companies that lack detailed geographic asset disclosures, creating significant blind spots in portfolio-level risk assessment.

Our market-based approach addresses these limitations by extracting systematic storm sensitivity patterns from historical stock market responses to major weather events. By analyzing how companies actually performed following 45 major storms over 24 years, we identify industries and sectors that demonstrate consistent financial vulnerability regardless of their disclosed asset locations.

This methodology captures the net financial impact of storm events after accounting for insurance recoveries, supply chain disruptions, demand shifts, and competitive repositioning—the full spectrum of factors that determine actual investor outcomes. The resulting damage functions provide portfolio-wide coverage, assigning statistically robust storm sensitivity parameters to all analyzed companies through industry-specific, sector-level, or pooled models depending on data availability and statistical significance.

For institutional investors holding diversified portfolios, this market-based framework offers material advantages over location-dependent approaches. Rather than requiring granular geographic asset data that most companies do not disclose, our methodology leverages publicly available stock price information to reveal systematic storm vulnerabilities across entire sectors. The approach also identifies not only companies with obvious physical exposure but also those facing hidden vulnerabilities through supply chain dependencies, customer base concentration, or business model sensitivity.

While location-based methods excel at quantifying direct physical damage for specific facilities, market-based approaches capture the broader financial materiality that drives investment performance—making them more relevant for the vast majority of equity investors whose risk assessment needs extend beyond site-specific physical exposure to portfolio-wide systematic vulnerability.

Context

Chronic vs acute

Physical climate risks are the direct impacts of changing climate conditions on businesses, infrastructure, and communities. These occur through gradual environmental shifts and sudden extreme weather events, and are categorized into two primary types. Chronic risks, involve long-term progressive changes, that unfold over decades, that can fundamentally alter operational conditions. They include, rising sea levels, increasing average temperatures, shifting precipitation patterns, and ocean acidification. Acute risks encompass sudden, severe weather events like hurricanes, floods, droughts, wildfires, and heatwaves, that can cause immediate, catastrophic damage to assets and disrupt operations.

Chronic risks typically allow for longer-term adaptation planning and the gradual adjustment of business strategies. Acute risks require immediate emergency response capabilities, and can result in sudden financial losses, supply chain disruptions, and operational shutdowns.

Both types of physical climate risk are becoming more significant as climate change intensifies. As such, organizations are needing to develop comprehensive risk management strategies that address both the slow-burning challenges of environmental transformation and the sharp shocks of extreme weather events.

> "Both types of physical climate risk (acute and chronic) are becoming more significant as climate change intensifies."

Temperature-based damage functions for chronic risk

The primary focus of most approaches to climate risk assessment in financial institutions and regulatory frameworks is chronic risks. This is done through the application of 'theoretical damage' functions that rely heavily on annual average temperature projections from climate models.

Temperature-based damage functions are mathematical relationships that quantify how economic output declines as global or regional temperatures rise above historical baselines. They serve as the core mechanism for translating climate change into economic impacts within integrated assessment models. These functions typically express economic damage as a percentage of Gross Domestic Product (GDP) loss for each degree of temperature increase. These estimates range widely, from 1% to 25% of global GDP for an incremental one-degree centigrade temperature rise, depending on the specification and calibration used.

Early formulations, like those in Nordhaus's Dynamic Integrated Climate-Economy (DICE) model, used relatively simple quadratic relationships between temperature and economic damage. However, these have been criticized for potentially underestimating impacts at higher temperature levels.

More recent damage functions, such as the one developed by Kotz et al. (2024) which has been adopted by the Network for Greening the Financial System (NGFS), incorporate additional climate variables beyond mean temperature, including temperature variability, precipitation patterns, and extreme weather indicators. They also account for the persistent effects of climate shocks, which can impact economic output for up to ten years after the initial temperature increase. Empirical studies like Burke et al. (2015) have developed nonlinear damage functions based on historical relationships between temperature and economic productivity. Their findings show that damages accelerate significantly at higher temperature levels, and affect poorer, lower-latitude countries disproportionately.

Despite their widespread use in climate economics and policy analysis, these functions remain highly uncertain and contentious, with substantial disagreement among researchers about appropriate functional forms, parameter values, and the extent to which they capture the full range of climate impacts on economic systems.

Temperature-centric approaches provide a tractable framework for chronic long-term risk. However, they miss the significant financial vulnerability of companies to acute, sudden extreme weather events that can cause immediate operational disruptions and concentrated losses, particularly in specific geographic regions or economic sectors.

Quantifying acute climate risk

The materiality of acute physical risks is underscored by recent evidence: according to the National Oceanic and Atmospheric Administration (NOAA), each of the last 14 years (2011-2024) has experienced 10 or more billion-dollar disasters. There were 27 billion-dollar disasters in 2024, which caused a total of $182.7 billion in damages, making it the fourth-costliest year on record.

The most widely used method of quantifying acute climate risk is catastrophe modeling (also known as "cat models"), which originated in the insurance industry in the 1980s. These models simulate thousands of plausible catastrophic event scenarios to probabilistically quantify expected damages. They use realistic parameters drawn from meteorological history, geology and geography, and geolocated asset data.

Practical limitations of 'location-based insurance methods'

Catastrophe models face significant practical limitations that constrain their widespread application:

- Geolocated inventories of assets are rarely available at meaningful scale. As such, they are fundamentally ill-suited to the needs of investors managing diversified portfolios across thousands of companies. Although, they may be better suited for insurance companies or banks assessing individual companies with concentrated geographic exposures.

- These models assess risk on an in-situ basis only, and do not consider the interconnectivity of assets. As such, they cannot capture how physical climate risk is inherited upstream and propagated downstream through supply chains.

Use-case limitations of 'location-based insurance methods'

Catastrophe models do not consider how individual companies, industries and financial markets respond to climate events. That means use of these models creates a critical disconnect between physical damage assessment and market valuation. In particular, they cannot account for the fact that:

- companies demonstrate different adaptation capabilities. For instance, firms with strong risk management practices adapt to losses from extreme events while smaller firms are more vulnerable (Benincasa et al., 2024).

- supply chain and competitive dynamics alter individual firm outcomes far beyond direct asset damage, as market positioning and operational flexibility become key determinants of financial impact. Recent evidence has revealed that some industries may even benefit from extreme weather through increased demand or reduced competition (Horvath and Moravcova, 2024).

- market efficiency varies significantly across industries, with some sectors successfully passing through climate costs to consumers while others are forced to absorb losses directly into margins.

- investor behavior, including sentiment shifts and risk perception changes, influence valuations beyond what fundamental damage assessment would suggest.

Fundamentally, cat models cannot account for the fact that climate sensitivity varies significantly based on industry, geography, business model, and adaptive capacity, limiting their effectiveness beyond specialized use cases.

Example:
Hurricane Harvey's supply chain cascade

In 2017, Hurricane Harvey flooded Houston, knocking out about one-third of the United States' petrochemical production and 18 oil refineries that compromised 20% of national refining capacity. The disruption cascaded across industries nationwide, affecting companies with no facilities anywhere near the flood zone.

Ford and General Motors had to idle manufacturing plants across multiple states because they couldn't get the plastics and chemicals needed for car production. Newell Brands (maker of Rubbermaid products) lowered their 2017 earnings guidance due to supply chain disruptions, forced to source resins from more expensive alternative suppliers. Electronics manufacturers, construction companies, food packaging firms, and pharmaceutical companies all faced similar disruptions, not because their facilities were damaged, but because the Gulf Coast produces 90% of America's base plastics and key chemical intermediates that flow into virtually every manufacturing supply chain.

Traditional geo-location models would have shown minimal direct risk to Ford's Michigan plants or Newell's facilities in Ohio or tech manufacturers in California. Yet these companies experienced some of their largest climate-related losses not from property damage, but from supply chain disruptions that lasted weeks longer than the storm itself.

The financial impact rippled far beyond the geographic footprint that current risk models assess, affecting companies whose facilities were thousands of miles from the actual climate event.

This is the systematic, enterprise-wide effects that investors need to understand but traditional tools systematically miss.

Market-based approaches for acute climate risk

Recent academic research has begun addressing this issue by examining actual market responses to extreme weather events. This growing body of literature provides crucial insights into how financial markets process and price physical climate risks.

Pagnottoni et al. (2022) provide a comprehensive global event analysis, examining 6,759 natural disasters across 104 countries and their impact on 27 global stock indexes from 2001-2019, using a five-day event window. Key findings show climatological and biological disasters produce the strongest market reactions, with European disasters generating the largest spillover effects on global markets.

Liu et al. (2024) complement this with a US-focused analysis with a comprehensive study of the NASDAQ 100, employing event study methodology on 526 climate disasters from 2000 to 2019. They find heterogeneous impacts across disaster types: biological and hydrological events have significantly negative impacts on stock returns, while climatic events paradoxically show positive impacts. This heterogeneity underscores the complexity of market responses to different types of extreme weather events.

Kruttli et al. (2025) provide the most comprehensive analysis to date, examining firm-level exposures to hurricanes from 1996 to 2019. They document that the stock options of firms with establishments in hurricane landfall regions exhibit implied volatility increases of 5-10%, with uncertainty persisting for up to three months after an event. Their analysis also reveals that investors systematically underestimated extreme weather uncertainty until Hurricane Sandy in 2012, which served as a learning event that improved subsequent market pricing.

Our approach

We extend recent research into market-based approaches to better quantify the market impact of extreme events for acute climate risk. Our approach departs from traditional event studies in three fundamental ways, designed to capture the full temporal and economic impact of major climate disasters for investors.

First, while conventional event studies employ short windows ([-1, +1] to [-30, +30] days) to isolate event impacts, we analyze four-week and 26-week post-event periods to capture the cascading nature of climate impacts. Climate disasters unfold over extended timeframes: initial damage assessments emerge in weeks 1-4, supply chain disruptions manifest in months 2-6, and competitive repositioning occurs through month 12 (Barrot & Sauvagnat, 2016; Carvalho et al., 2021). Our four-week window captures immediate market reactions, while the 26-week window encompasses full business cycle impacts including insurance settlements, demand normalization, and strategic adaptations. This extended timeframe finds empirical support in the climate finance literature: Dessaint and Matray (2017) document hurricane attention effects persisting multiple quarters, while Kruttli et al. (2021) show option price impacts extending beyond six months post-hurricane.

Second, rather than calculating abnormal returns against pre-event market models, we benchmark firm performance directly against the S&P 500 over the same post-event period. This approach isolates climate-specific impacts from broader market movements while accounting for macroeconomic conditions that simultaneously affect both disaster-exposed firms and the broader market.

Third, we restrict our analysis to economically significant events exceeding $5 billion in damages. This threshold ensures we examine disasters with material economy-wide impacts, while reducing noise from smaller events unlikely to generate detectable market signals. Hurricane Katrina exemplifies why this materiality threshold matters: initial damage estimates of $10-25 billion eventually reached $125 billion as disruptions cascaded through the economy over the following year (Belasen & Polachek, 2008; Vigdor, 2008).

A practical market-driven approach for investors

Our approach offers three key advantages to the traditional approaches used by providers:

Market-derived climate sensitivity

Rather than relying on asset-level data and theoretical models of climate vulnerability, we extract empirical climate sensitivity parameters from actual stock market responses to historical extreme weather events. This approach captures the market's integrated assessment of direct physical damage and broader operational and value chain disruptions, thus incorporating the full spectrum of factors that determine actual financial outcomes.

Hierarchical Bayesian modeling structure

Recognizing that individual companies have varying levels of historical exposure data, we employ a hierarchical Bayesian approach that pools information across industry and sector levels when company-specific data is insufficient. This methodology addresses the fundamental challenge of limited observations while accounting for the dramatic heterogeneity in climate responses across industries.

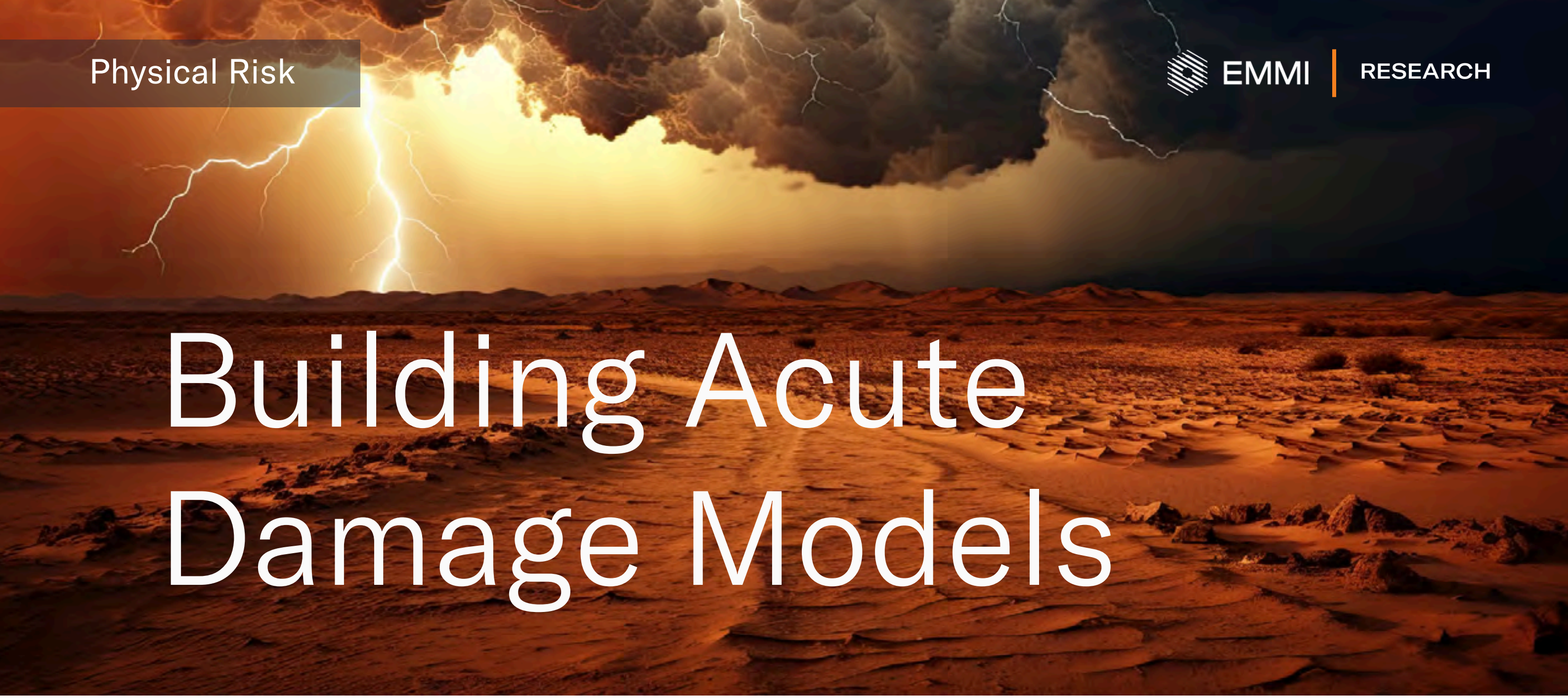
Integration with forward-looking scenarios

We systematically link historical market-derived sensitivities to forward-looking climate projections, providing a comprehensive framework that spans from empirical analysis to scenario-based risk assessment. This bridges the gap between backward-looking market evidence and the forward-looking climate risk analysis required for regulatory compliance and strategic planning.

The resulting framework provides a quantitative basis for assessing company-specific acute climate risk exposure across different climate scenarios and time horizons, grounded in how markets have actually responded to extreme weather events in the past. By incorporating market dynamics, adaptation responses, and investor behavior, our approach captures the complex mediating factors between physical climate events and financial outcomes that existing methodologies miss.

This research contributes to the rapidly evolving field of climate finance by offering a methodology that bridges physical climate science and financial market analysis, providing practitioners with tools that reflect market reality rather than theoretical abstractions. As extreme weather events continue to increase in frequency and severity, understanding how markets price and respond to these risks becomes ever more critical for investment decision-making, risk management, and climate-related financial disclosure.

[1] https://www.climate.gov/news-features/blogs/beyond-data/2024-active-year-us-billion-dollar-weather-and-climate-disasters



Building Acute Damage Models

A history of extremes: Using the United States as the foundation

We focus on developing market-based acute climate risk models in the United States (US) for a variety of reasons. First, the US is disproportionately hit by extreme events, thereby allowing the best chance for a market signal to emerge. Some 84% of the 25 most catastrophic weather-disasters globally have occurred in the US. The National Centers for Environmental Information (NCEI) of NOAA have documented 403 billion-dollar (or more) disasters from 1980 to 2024, totaling $2.915 trillion in damages. Second, combining the NCEI dataset with FactSet market data enables robust empirical analysis unavailable in other markets. Third, the depth and liquidity of US markets, and the extensive analyst coverage, ensure efficient price discovery and information incorporation. Fourth, enhanced regulatory reporting requirements provide the corporate exposure data necessary for meaningful analysis. Finally, the geographic diversity of climate hazards across US regions tests model robustness and generalizability.

Models calibrated on US data can subsequently be scaled globally, using relative risk ratios and local hazard projections, as demonstrated by similar approaches in emerging markets documented by Hong et al. (2023) and Chen et al. (2024).

Analysis of billion-dollar weather disasters in the US from the year 2000 reveals escalating trends in both frequency and economic impact. The data demonstrates substantial year-to-year variability in disaster costs, with certain years experiencing catastrophic losses far exceeding typical annual damages. The year 2017 was the most destructive period on record, generating approximately $360 billion in damages, followed by 2005 with $260 billion in losses. Hurricane events were the primary driver of these extreme damage years.

The composition of disaster types shows hurricanes are the dominant source of economic damage, though other categories contribute meaningfully to annual totals. In recent years, wildfire damage has emerged as an increasingly significant factor, particularly from 2018 to 2020. Drought, flooding, severe storms, and winter storms maintain consistent presence throughout the analysis period, contributing to baseline annual damage totals.

Long-term trend analysis, using three-year rolling averages, reveals patterns of escalation. The frequency of billion-dollar disasters has seen a statistically significant upward trend, rising from approximately 1.5 events annually in the early 2000s to over five events per year by 2020. Similarly, total economic damages demonstrate an increasing trajectory over the analysis period, though with greater volatility than event frequency. The trend in total damages peaked between 2017 and 2019, before experiencing a moderate decline.

> “Some 84% of the 25 most catastrophic weather-disasters globally have occurred in the US.”

Trends

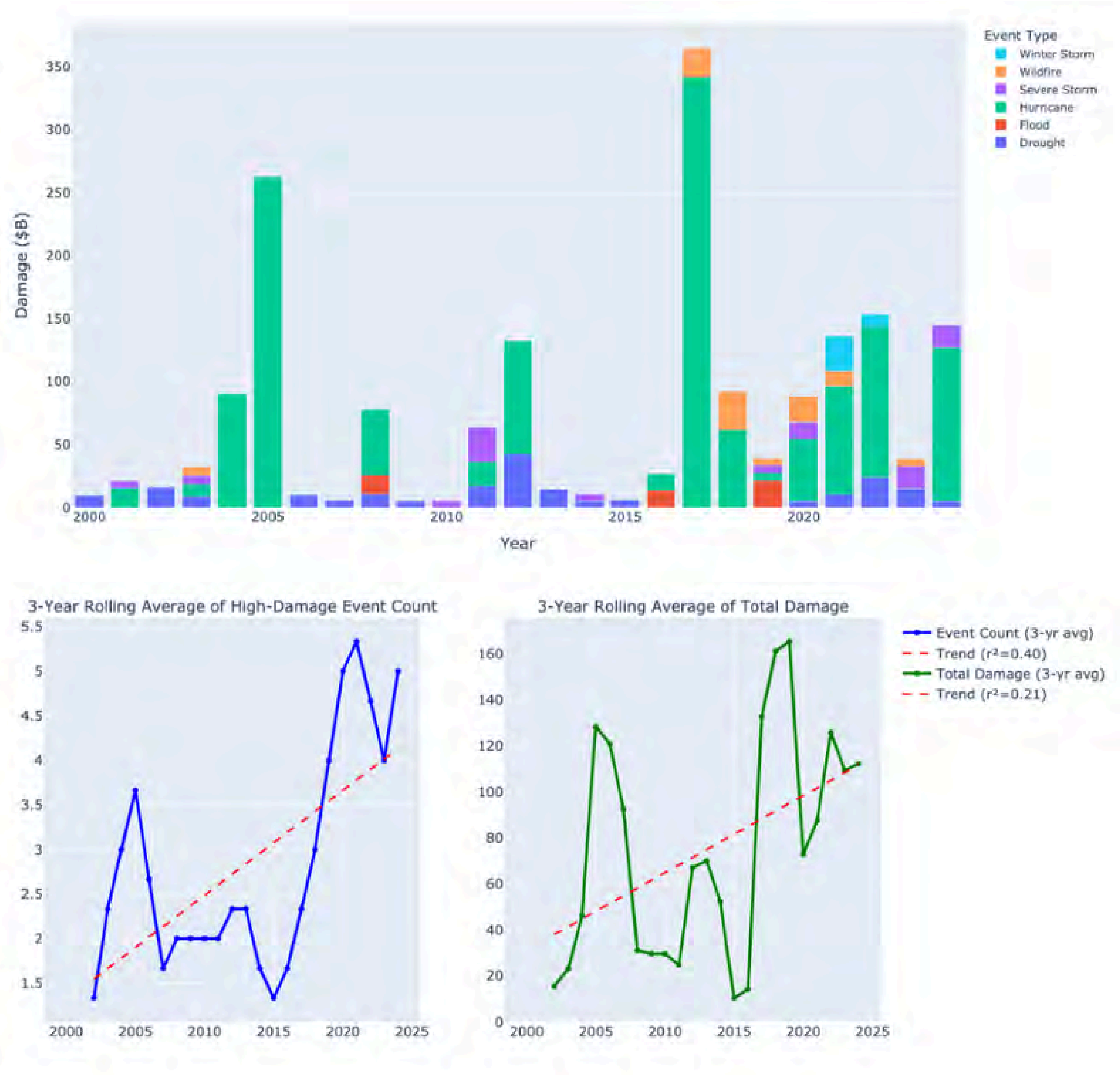


Chart: Economic damage of and trends in billion-dollar weather and climate disasters in the US from 2000 to 2024, with costs adjusted for inflation.

Geographic patterns

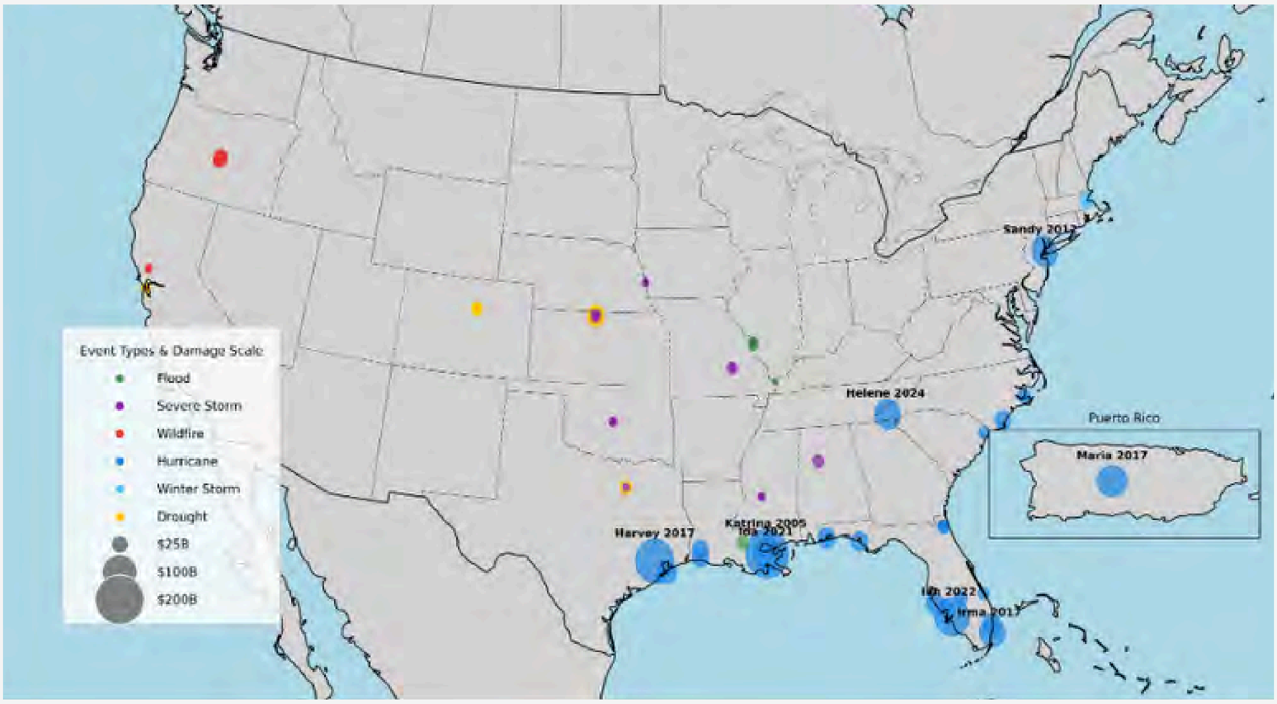


Chart: Geographic visualization of billion-dollar weather and climate disasters across the US from 2000 to 2024, with circle sizes representing CPI-adjusted damage amounts.

The spatial distribution of extreme weather events reveals several critical patterns in disaster occurrence and impact.

The clustering of large blue circles along coastal regions underscores hurricanes as the predominant driver of billion-dollar disasters. The most striking feature is the concentration of massive hurricane damage along the Gulf Coast and Eastern Seaboard. Hurricane Harvey (2017) appears as the largest circle, centered over Texas, reflecting its catastrophic, more than $125 billion, impact. Other major hurricanes are clearly visible: Katrina (2005) affecting Louisiana and Mississippi, Sandy (2012) impacting the Northeast, and Maria (2017) devastating Puerto Rico (shown in the inset).

The interior regions show a different disaster profile, with severe storms (purple dots) scattered across the Midwest and Central Plains, particularly concentrated in states like Missouri, Arkansas, and surrounding areas. Wildfires (red dots) are notably present in California and the Pacific Northwest, while drought impacts (yellow dots) appear in states like Colorado and Texas. A winter storm (light blue) is marked in the Northeastern region, and flood events (green dots) are distributed across various states.

The map effectively illustrates how different regions face distinct climate-related threats: coastal areas bear the brunt of hurricane damage, the central states frequently experience severe storms and flooding, the West faces wildfire risks, and drought affects multiple regions. This geographic distribution of disasters by type provides crucial context for understanding regional vulnerability patterns and the varying nature of climate risks across the US.

Major events

Hurricane Katrina (2005) stands as the most destructive disaster, causing $202 billion in damages—significantly exceeding all other events. Hurricane Harvey (2017) ranks second at $161.3 billion, followed by Hurricane Ian (2022) at $120.7 billion and Hurricane Maria (2017) at $116.1 billion. As noted before, 2017 was a particularly devastating year, with three hurricanes (Harvey, Maria, and Irma) making the 'top 10' list and collectively causing over $340 billion in damages. Hurricane Sandy (2012), which impacted the densely populated Northeast, resulted in $89.8 billion in damages, while more recent hurricanes like Ida (2021) and Helene (2024) caused $86.1 billion and $79.5 billion respectively. Notably, nine of the ten costliest disasters are hurricanes, with only one exception: the 2012 US Drought/Heat Wave ranks tenth at $42.3 billion

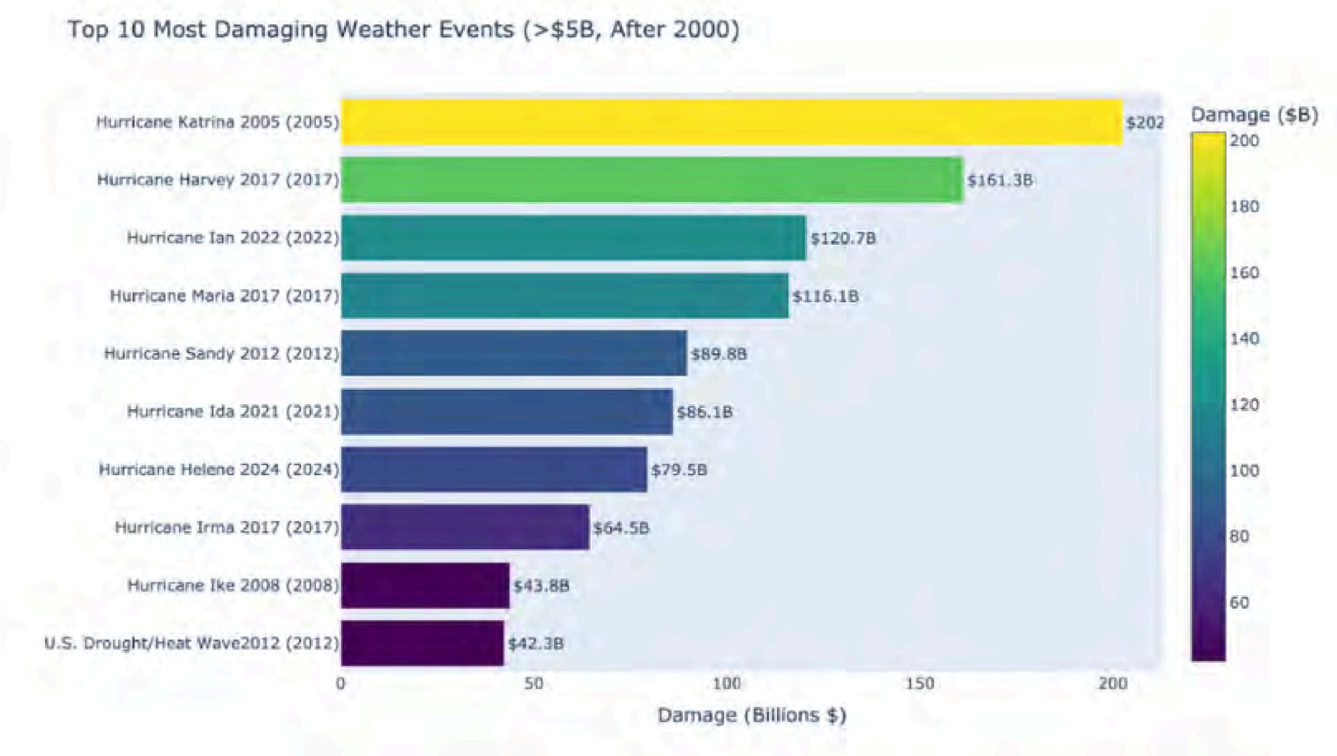


Chart: Top ten most economically damaging weather events in the US since 2000 adjusted for inflation.

> ... 2017 was a particularly devastating year, ... collectively causing over $340 billion in damages."

Data and methods

Event selection

To quantify the market response to major weather disasters, we focus on stock performance after major disasters that have discrete, short-duration impact windows—specifically tropical cyclones (hurricanes), floods, and wildfires that exceeded $5 billion in damages. These event types typically concentrate their economic damage within a matter of days, providing clear temporal boundaries for market impact assessment.

We exclude droughts from this analysis despite their substantial economic costs, as their gradual onset and extended duration from months to years present methodological challenges. Unlike acute disasters with well-defined start and end dates, droughts lack clear baseline and post-event demarcation points necessary for robust market response quantification. The protracted nature of drought impacts also makes it difficult to isolate market reactions attributable to the disaster from broader economic trends and seasonal variations.

By constraining our analysis to acute-onset disasters, we can more precisely measure how financial markets price in and recover from catastrophic weather events, providing insights into both immediate market volatility and longer-term economic resilience following major climate-related disasters.

“By constraining our analysis to acute-onset disasters, we can more precisely measure how financial markets price in and recover from catastrophic weather events … ”

Identifying vulnerable industries, sectors and companies

This study employs a systematic approach to identify industries and sectors with the highest exposure to weather and climate-related risks. Weather exposure is conceptualized through four primary transmission mechanisms: (1) direct physical asset vulnerability, (2) operational disruption channels, (3) supply chain interdependencies, and (4) geographic concentration of business activities in weather-prone regions. This framework builds upon catastrophe risk literature that distinguishes between immediate physical impacts and cascading economic effects (Strobl, 2011; Hsiang & Narita, 2012).

Selection criteria

Industries were evaluated against the following criteria to determine weather-exposure intensity:

Direct physical impact channels: Sectors where weather events directly affect core business operations, asset values, or production processes. This includes agricultural activities vulnerable to drought, flooding, and temperature extremes, as well as real estate sectors facing direct property damage from hurricanes, wildfires, and flooding.

Infrastructure vulnerability: Industries dependent on weather-sensitive infrastructure networks, particularly utilities (electric, water, alternative energy generation) and transportation sectors (airlines, shipping, rail, trucking) where operations are frequently disrupted by adverse weather conditions.

Geographic risk concentration: Sectors with significant asset concentrations in weather-prone regions, such as Gulf Coast energy infrastructure vulnerable to hurricanes, or western real estate exposed to wildfire risk.

Supply chain dependencies: Industries whose operations depend on weather-sensitive inputs or transportation networks, including industrial manufacturing, chemicals, and construction materials where weather disruptions cascade through supply chains.

Financial risk concentration: Insurance sectors that directly underwrite weather-related risks and experience concentrated claims during major weather events.

Industry classification results

The methodology identified 43 industry classifications across eight major sectors. Agriculture represents the largest component (nine industries), reflecting its direct dependence on weather conditions for crop production, livestock management, and food processing. Real Estate follows with five industries, encompassing homebuilding, development, Real Estate Investment Trusts (REITs), and hospitality sectors vulnerable to direct property damage and location-specific risks.

Utilities (four industries) and Energy (seven industries) feature prominently due to infrastructure vulnerability and geographic concentration in weather-exposed regions. The inclusion of Transportation (five industries) and Industrial (eight industries) sectors reflects their supply chain dependencies and operational disruption channels. Insurance (five industries) represents the financial intermediation of weather risks.

Company selection methodology

Following industry identification, the ten largest companies by market capitalization were selected from each identified industry classification. This approach ensures that the sample captures:

- the most systemically important entities within each sector
- companies with sufficient market liquidity for meaningful risk assessment
- firms with comprehensive financial reporting and disclosure requirements
- representative coverage of major market participants across weather-exposed industries

Validation and limitations

This two-stage selection process provides a systematic approach to weather exposure assessment while maintaining focus on economically significant market participants. The market capitalization-based selection may introduce bias toward larger, more diversified companies that may have superior risk management capabilities compared to smaller, more specialized firms. However, this approach ensures sample relevance for institutional investors and provides adequate statistical power for risk assessment across weather-exposed sectors.

The classification focuses on industries with direct operational exposure to weather events, consistent with acute physical risk assessment frameworks used in climate finance (Fiedler et al., 2021), while the market cap-weighted selection ensures economic representativeness within the identified universe.

Historical stock extraction

For each extreme weather event (e), we establish three critical time points: the baseline date (t_0) as the most recent trading date prior to event start, the short-term assessment date (t_4) at four weeks post-baseline capturing immediate market reactions, and the long-term assessment date (t_{26}) at twenty-six weeks post-baseline, reflecting full economic impacts including reconstruction and adaptation.

For each stock (i) affected by event e, we calculate both absolute and relative performance metrics:

Absolute Performance:
$P_4(i,e) = [Price(i,t_4)/ Price(i,t_0) - 1] \times 100$
$P_{26}(i,e) = [Price(i,t_{26})/ Price(i,t_0) - 1] \times 100$

Relative Performance:
$RP_{26}(i,e) = P_{26}(i,e) - P26(S\&P500,e)$

The 26-week relative performance metric serves as our primary dependent variable, controlling for broader market movements while capturing the full lifecycle of event impacts.

Table: Sector coverage and event exposure

Sector	Companies	Event Observations	Industries	Avg. Observations per Company
Agriculture	44	16,355	7	372
Industrial	51	15,326	6	300
Energy	39	14,422	6	370
Real Estate	41	13,185	5	321
Transportation	36	11,726	5	326
Insurance	33	10,891	4	330
Utilities	31	10,455	4	337

To ensure analytical robustness, we exclude financial crisis years 2008-2009 and pandemic years 2020-2021, to avoid conflating climate impacts with systemic disruptions (global financial crisis and pandemic). We retain only events with damages exceeding $5 billion for final modeling to focus on events with material financial impacts.

Table: Number of company-event observations used

Event Type	Number of Events	% of Events	Company-Event Observations	% of Company-Event Observations	Avg. Companies per Event
Tropical Cyclone	32	71.1%	8,311	70.9%	259.7
Wildfire	7	15.6%	2,210	18.8%	315.7
Flood	6	13.3%	1,204	10.3%	200.7
Total	45	100.0%	11,725	100.0%	260.6

This filtered analysis of 11,725 company-event observations provides a focused view of market responses to disasters with discrete, short-duration impact windows, enabling more precise measurement of immediate market volatility and recovery patterns.

Tropical Cyclones constitute the overwhelming majority of acute-onset disasters, representing 71.1% of events and 70.9% of all company-event observations in the dataset. This dominance reflects both their frequency and severe economic impact.

Industry-specific bayesian modeling

We implement winsorization at the 10th and 90th percentiles for both damage and performance variables to preserve general relationships while reducing extreme observation influence for each industry or sector.

For each industry (j), we specify a log-linear relationship between climate damages and equity performance:

$Y(i,e) = \beta_{0j} + \beta_{1j} \times \log(Damage\_e) + \varepsilon(i,e)$

Where Y(i,e) represents 26-week relative performance, Damage_e denotes economic damage in billions of US dollars, β_{1j} captures industry sensitivity to log-damages, and $\varepsilon(i,e) \sim N(0, \sigma^2_j)$ represents residual error.

We use a statistical method called 'conjugate prior' Bayesian regression, with weakly informative priors to make predictions while accounting for uncertainty. Instead of just finding one "best" answer, this approach considers many possible answers and weighs the likelihood of each one. We start with some basic assumptions about what the answer might be (called "priors") - but we keep these assumptions very loose so they don't overly influence our results.

We then use the actual data to update our beliefs and get a range of possible answers. We run this process 10,000 times to get a good picture of how confident we can be in our predictions, and to understand what the uncertainty looks like.

An industry model achieves "robust" classification if it passes three tests:

1. Statistical confidence: We need to be at least 95% sure that the relationship we found is real and not just due to chance. This means if we see a positive or negative trend, we're very confident it's actually there.
2. Enough data: We need at least ten separate examples to draw conclusions from. Too few examples make it hard to trust the pattern.
3. Meaningful impact: The model needs to explain at least 10% of what's happening in the real world. If it explains less than that, it's probably not useful for making decisions.

We tested our robust models to make sure they work on new data and aren't too sensitive to our assumptions.

Testing on new data

We split our data into five groups and trained the model on four groups, then tested it on the fifth group. We repeated this process for each group. The models performed about 15-20% worse on the new data compared to the original data, which is normal and acceptable. The key relationships we found stayed very consistent across all tests (varying by less than 10%).

Testing our assumptions

We also checked whether our results would change if we made different choices in our analysis:

- We tried different starting assumptions about what the answer might be - this barely changed our results (less than 5% difference)
- We tried different ways of handling extreme data points - this also had minimal impact (less than 8% difference)

Results

Damage models for vulnerable industries

The analysis of 26-week post-event performance reveals that most industries exhibit a negative performance due to storms. Statistically, six out of 37 industries demonstrate significant negative relationships between storm damages and stock performance.

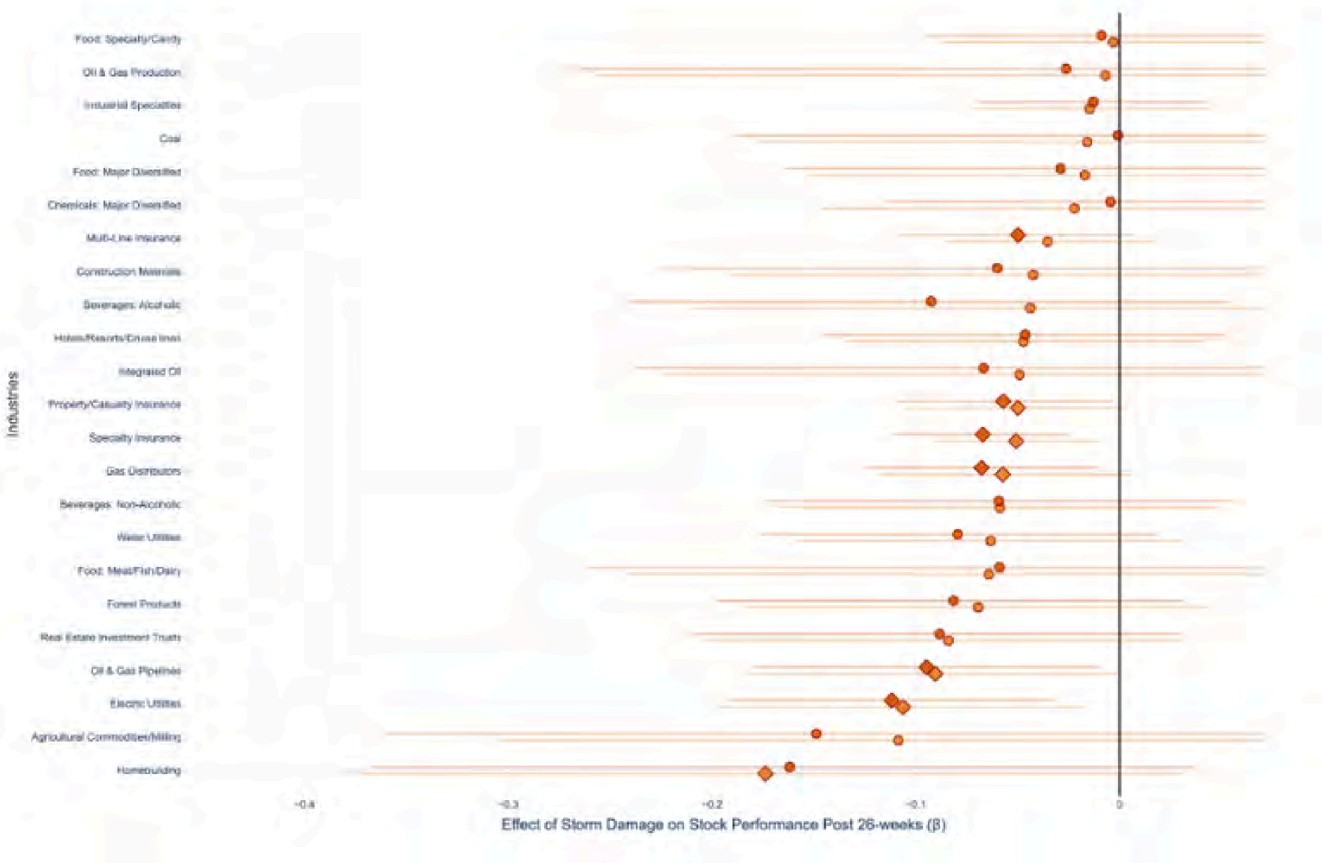


Chart: Effect of storm damage on stock performance (β) across industries at the 26-week post-event window, with 95% confidence intervals shown as horizontal lines and point estimates marked by circles or diamonds. The vertical dashed line at β = 0 represents no effect, with negative values indicating that storm damages are associated with worse stock performance. The colors represent 0-week window (darker orange) and -1 week event window (lighter orange).

The industries showing significant negative storm effects span multiple sectors, with effect sizes ranging from small to medium in magnitude. Homebuilding exhibits the strongest negative relationship at β = -0.174, representing approximately a 0.17 percentage point decrease in stock performance for each additional billion dollars of catastrophe damage. The utilities sector demonstrates notable vulnerability through, with Electric Utilities at β = -0.106. The energy infrastructure sectors show consistent negative impacts via Oil & Gas Pipelines (β = -0.090) and Gas Distributors (β = -0.057). The insurance sector maintains significant vulnerability with both Specialty Insurance (β = -0.051) and Property/Casualty Insurance (β = -0.050) showing negative relationships. This pattern reinforces that climate damages create heterogeneous impacts across the economy, with vulnerability concentrated in specific industries that face direct physical exposure, infrastructure damage, or claims concentration.

Model fit and interpretation

Our R^2 values for robust models range from 12% to 24% at the 26-week horizon, indicating meaningful explanatory power for climate damage relationships. These values should be interpreted within the context of financial event study methodology, where isolating a single factor is inherently challenging: companies simultaneously face numerous operational, competitive, and macroeconomic shocks over extended periods. Standard event studies often report R^2 below 0.10 (MacKinlay, 1997), while Hong et al. (2019) document R^2 of 0.08-0.15 for climate risk regressions. An R^2 of 0.20 indicates that climate events explain 20% of excess return variation over the event window, an economically substantial effect for a single explanatory factor.

Our approach of benchmarking against the S&P 500 helps remove broad non-climate related market shifts, allowing us to better isolate climate-specific impacts. However, our objective is identifying robust causal relationships between climate events and financial outcomes, not building comprehensive return prediction models. The Bayesian framework provides probabilistic interpretation of effects, with all significant results showing greater than 95% probability that the true effect is negative, ensuring conservative identification of genuine climate vulnerabilities.

While we observed negative storm damage coefficients across most industries we examined, the effects were statistically significant for only six industries. Importantly, these six industries across utilities, insurance, energy and real estate have clear exposures to wider storm risks through physical infrastructure, supply chains, and geographic concentration. This alignment between statistical significance and economic intuition provides additional validation of our methodological approach.

Damage models for vulnerable sectors

To complement the industry-specific analysis, we conducted sector-level pooled regression for industries that did not demonstrate individual statistical robustness. This approach increases statistical power by combining observations across related industries within each sector, revealing broader sector-wide patterns.

Five sectors achieve statistical significance for negative relationships in the pooled analysis. Agriculture emerges with the largest sector-level effect at $\beta = -0.116$, confirming vulnerability to weather-related disruptions affecting crop yields and livestock operations. Real Estate Development shows the strongest statistical evidence with $\beta = -0.082$ validating the concentration of storm vulnerability identified in the industry-specific analysis. The Utilities sector demonstrates significant negative effects at $\beta = -0.052$ confirming systematic vulnerability to infrastructure damage and service disruption. Finance achieves high statistical certainty with $\beta = -0.040$ driven primarily by insurance industries' direct exposure to storm-related claims.

The remaining sectors—Industrial Services, Transportation, Producer Manufacturing, Consumer Services, Energy Minerals, and Process Industries—show inconclusive evidence with confidence intervals spanning both positive and negative territory and probabilities near 50%, indicating genuine uncertainty in their sector-wide storm damage relationships. These sectors likely contain a mix of industries with offsetting exposures, where some benefit from reconstruction opportunities while others face supply chain disruptions or demand volatility.

Hierarchical model framework for wider market

We implement a hierarchical decision framework that prioritizes specificity while ensuring coverage. For each industry (j), if the industry has a robust model, we assign β_{1j}. Otherwise, if the parent sector has a robust model, we assign β_{1s}. For all remaining cases, we assign β_1_pooled, which is model for all industries not found to be significant.

The hierarchical synthesis produces the following model assignment distribution across 364 companies: Industry-specific models cover 70 companies (19.2%) in Real Estate, Utilities, and Insurance sectors. Sector-level models apply to 89 companies (24.5%) primarily in Agriculture and additional Real Estate firms. The pooled model covers 205 companies (56.3%) across Energy, Industrial, Transportation, and other sectors.

Example:
Market analysis for electric utilities

The Electric Utilities industry demonstrates significant storm vulnerability at the 26-week post-event window with an effect size of β = -0.109 (95% confidence interval: -0.190 to -0.027, $P(\beta < 0)$ = 0.994), representing a medium-magnitude negative relationship that explains 24.3% of stock performance variance during storm events. The chart below illustrates the industry's storm sensitivity across 23 events, showing a consistent negative trend where each additional billion dollars of catastrophe damage corresponds to approximately a 0.11 percentage point decrease in electric utility stock performance relative to the S&P 500 over the 26-week period following extreme weather events. The scatter plot reveals vulnerability across multiple storm hazard types, with tropical cyclones (blue circles) creating the most frequent impacts, while wildfires (red stars) and floods (green diamonds) also generate notable negative performance responses. This is particularly evident in events causing damages of $20-40 billion, where several data points cluster in negative performance territory exceeding -10%.

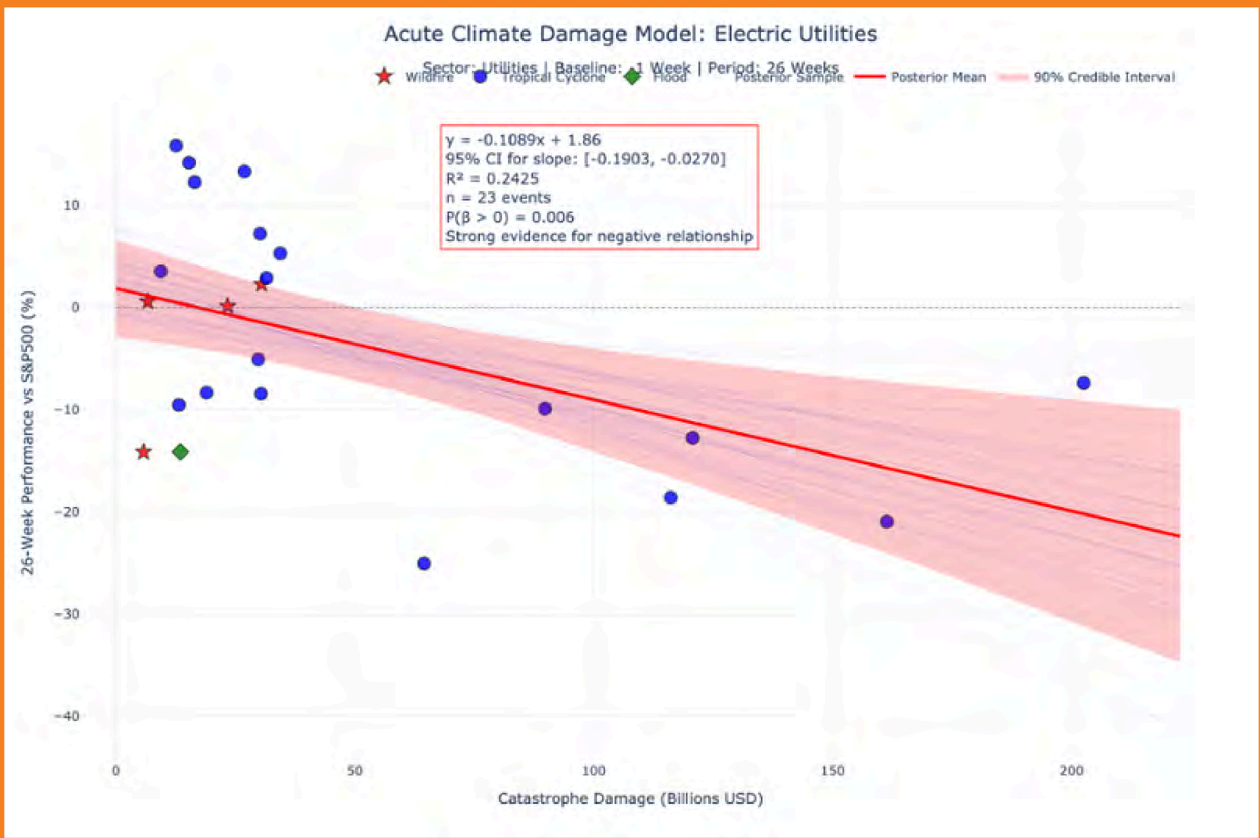


Chart: Electric Utilities Industry Storm Damage Model

The industry's storm sensitivity reflects multiple direct exposure pathways to extreme weather events. Electric Utilities face grid disruptions from high winds, flooding of substations, and wildfire-induced power shutoffs, while simultaneously experiencing peak demand during extreme temperature events. Infrastructure damage from tropical cyclones includes downed transmission lines, damaged transformers, and flooded electrical equipment, requiring substantial emergency response costs and accelerated infrastructure replacement. The essential nature of electrical services during and after disasters creates dual pressures: utilities must maintain operations under extreme stress while facing concentrated capital expenditures for system restoration.

Individual company analysis reveals widespread storm sensitivity within the Electric Utilities sector, though with notable heterogeneity in vulnerability magnitudes. Duke Energy Corporation (DUK), one of the largest electric utilities in the US, exemplifies this systematic exposure with $\beta = -0.140$ (95% confidence interval: -0.245 to -0.035, $P(\beta < 0) = 0.995$, $R^2 = 0.241$), as shown below.

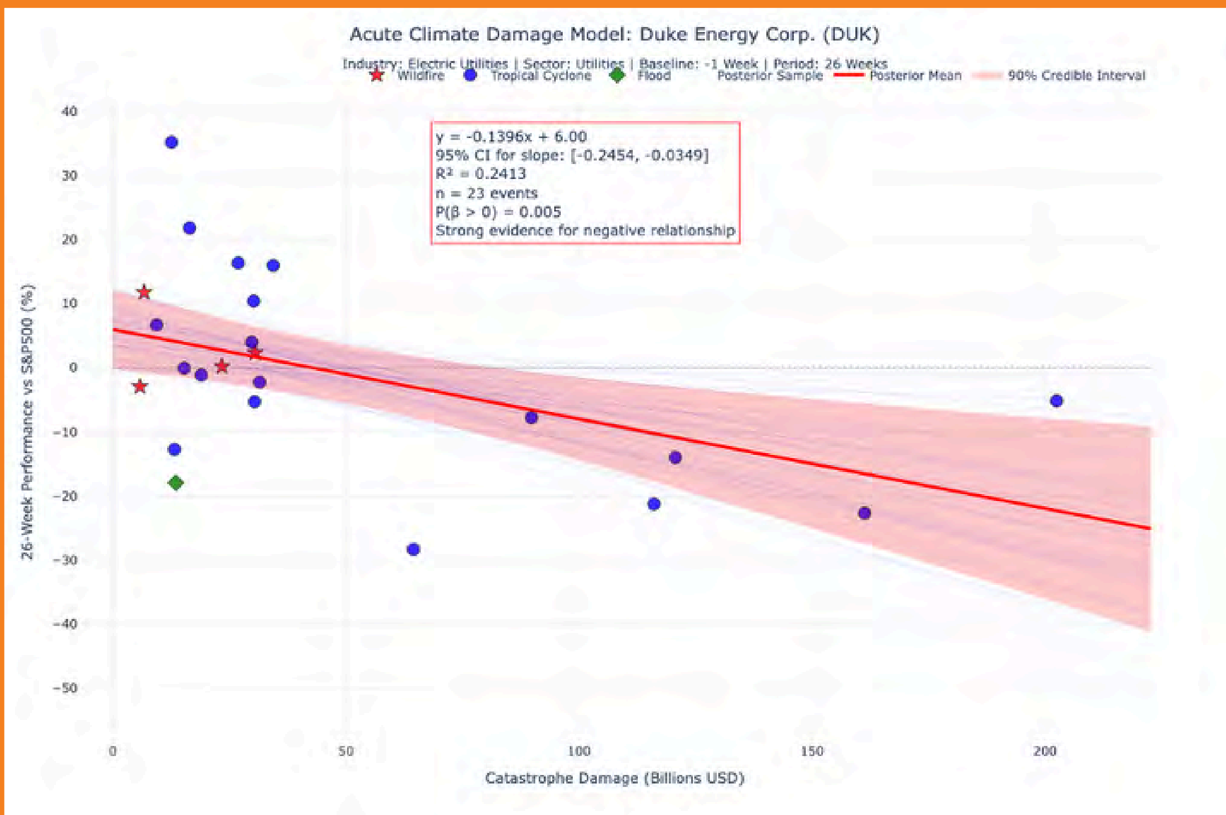


Chart: Duke Energy Corporation Storm Damage Model

Duke Energy’s service territories span the Carolinas, Florida, Ohio, Indiana, and Kentucky, regions with significant exposure to both hurricane activity along the Atlantic coast and severe thunderstorms in the Midwest. The company's storm damage relationship shows statistical strength, with 99.5% probability of negative effects and the model explaining 24.1% of DUK’s excess return variation over the 26-week periods following major storm events. Duke's scatter plot demonstrates vulnerability across the full range of storm magnitudes, from smaller events under $20 billion causing 0-10% negative performance to major hurricanes exceeding $100 billion in damages generating performance declines ranging from -10% to -30%. The concentration of DUK’s data points below the zero line across diverse storm types and magnitudes confirms systematic rather than idiosyncratic vulnerability. The company’s coastal exposure particularly amplifies hurricane vulnerability—it faced substantial restoration costs and infrastructure replacement needs following hurricanes Florence (2018), Michael (2018), and Ian (2022), visible in the scatter plot as significant negative performance outliers.

The 26-week measurement window captures the full impact cycle of storm events on electric utilities, including immediate restoration costs, longer-term infrastructure replacement needs, regulatory proceedings related to disaster response adequacy, and potential prudency reviews of storm-related capital expenditures. This timeframe allows markets to process quarterly earnings reports that reveal the actual financial magnitude of disaster impacts, including insurance recoveries, cost deferrals through regulatory mechanisms, and the effectiveness of grid hardening investments in mitigating damage. Duke Energy's results demonstrate that even with sophisticated emergency response capabilities and regulatory cost recovery mechanisms, major storm events create material negative impacts on utility valuations that persist throughout the six-month post-event window.

The statistical robustness of the Electric Utilities model, with 99.4% probability of a negative relationship across the full industry, reflects the sector's systematic vulnerability to acute storm events. Unlike industries where storm impacts may be offset by increased demand or competitive

“The 26-week measurement window captures the full impact cycle of storm events on electric utilities ... ”

advantages, Electric Utilities face relatively pure downside exposure: disasters create costs without corresponding revenue opportunities, as rate structures typically lag infrastructure replacement needs and regulatory frameworks may limit utilities' ability to immediately recover storm-related expenditures. Duke Energy's 99.5% probability of negative effects exemplifies this pattern at the individual company level, demonstrating that even the largest, most diversified utilities with extensive experience in storm response face consistent financial headwinds from major weather disasters.

The R^2 value of 24.3% for the industry-level model indicates that storm damages explain approximately one-quarter of excess return variation in Electric Utilities over the 26-week post-event period. This represents substantial explanatory power for a single factor, despite the fact that utility stocks face numerous other influences including interest rate changes, regulatory developments, and fuel cost fluctuations. Duke Energy's comparable R^2 of 24.1% reinforces this finding at the company level, suggesting that storm vulnerability is not diluted by firm-specific factors, but rather represents a fundamental systematic risk across the sector.

Geographic concentration of utility service territories amplifies storm vulnerability for certain companies. Duke Energy's multi-state footprint creates both diversification benefits and concentrated coastal exposure. Severe weather in one region may be offset by stable conditions elsewhere, the company's substantial operations in hurricane-prone Carolinas and Florida create unavoidable exposure to the most damaging tropical cyclones. Utilities operating exclusively in hurricane-prone coastal regions face even more concentrated exposure, while those serving wildfire-prone western territories encounter increasing risk from both direct fire damage and liability for fire ignition. This geographic specificity creates heterogeneous storm exposure across individual utility companies, though the industry-level model captures the average systematic vulnerability across the sector.

"Geographic concentration of utility service territories amplifies storm vulnerability for certain companies. Duke Energy's multi-state footprint creates both diversification benefits and concentrated coastal exposure."

Image source: https://www.cfdc.org/investor/duke-energy/

Conclusion

Our research introduces a market-based methodology for quantifying storm vulnerability that addresses a critical gap in existing climate risk assessment frameworks.

The market-based approach addresses the limitations of traditional location-based approaches by extracting systematic storm sensitivity patterns from historical stock market responses to major weather events.

The framework offers material advantages for institutional investors holding diversified portfolios. It identifies not only companies with obvious physical exposure but also those facing hidden vulnerabilities through supply chain dependencies, customer base concentration, or business model sensitivity. While location-based methods excel at quantifying direct physical damage for specific facilities, market-based approaches capture the broader financial materiality that drives investment performance—making them more relevant for the vast majority of equity investors whose risk assessment needs extend beyond site-specific physical exposure to portfolio-wide systematic vulnerability.

For a full list of limitations and FAQs please CLICK HERE

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About Emmi

Climate risk, built for investors

Emmi provides comprehensive climate risk intelligence for investors. Our datasets cover emissions, transition and physical risk across public and private markets, covering all major asset classes and driving 100% portfolio coverage.

Built on a consistent methodology, Emmi delivers the transparency and customisation investors need to make better investment decisions, meet climate disclosure requirements, and align with regulatory and mandate expectations.

Emmi is founded on a simple idea: mobilising capital is the fastest path to decarbonisation. By quantifying climate risk exposure at scale, we enable the financial sector to allocate capital more efficiently toward climate-aligned outcomes.

To meet this need, we built Carbon Diagnostics - decision-useful climate insights, delivered at scale.

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