Who Bears Climate Risk? Differential Impacts on Public and Private Firms

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Abstract

Climate disclosure standards, including the ISSB's IFRS S1 and S2, primarily target publicly traded firms. We test whether this focus aligns with where climate risk actually falls. Using establishment-level data covering 8.9 million private and 13,513 public parent firms matched to over two decades of federal disaster declarations, we find a striking divergence. Public firms experience no significant operating performance effects from climate disasters, while private firms experience sales declines of 0.7% on average at their local operations in disaster-affected counties. The declines are concentrated in manufacturing, retail, chemicals, and healthcare, and persist for several years in capital-intensive industries. We examine geographic diversification and access to credit as candidate mechanisms. Both partially explain the public–private differential, but neither mechanism protects firms in capital-intensive industries that cannot easily relocate production. The firms most exposed to climate disasters are private firms in specific industries, precisely those for which investors lack standardized climate risk information. Our findings inform the international debate about extending sustainability disclosure beyond publicly traded firms.

Keywords: ESG, climate risk, natural disasters, private firms, disclosure regulation, geographic diversification, operating performance.
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1 Introduction

Climate risk disclosure has become one of the most contentious regulatory debates of our time. In March 2024, the SEC finalized rules requiring public companies to disclose material climate-related risks, including physical risks from severe weather events.[1] The rules immediately faced legal challenges from sixteen Republican state Attorneys General who argue climate risk is "too speculative" to meet materiality thresholds.[2] Proponents counter that investors "representing tens of trillions of dollars" need standardized climate information to allocate capital efficiently. Globally, the International Sustainability Standards Board (ISSB) has established IFRS S1 and S2 as a baseline for climate-related disclosures, with over 30 jurisdictions now adopting or developing regulations based on these standards (IFRS Foundation, 2025; S&P Global, 2026). The National Oceanic and Atmospheric Administration (NOAA) estimates that over the past decade, the U.S. has experienced $1.2 trillion in damages from 173 separate billion-dollar disasters (NOAA, 2024), suggesting the economic stakes are substantial. Yet a fundamental question remains unresolved: do climate disasters actually affect firm operating performance, and if so, which firms bear these costs?

While Europe has taken the lead in mandating climate disclosures through the Corporate Sustainability Reporting Directive (CSRD), building on prior requirements for large firms (e.g., the 2003 EC Accounting Directive; Bernard et al., 2018; Ortiz-Martínez et al., 2023), most climate disclosure regulations, including those based on ISSB standards, focus primarily on publicly traded companies. Some jurisdictions are beginning to extend requirements to private firms. For instance, Singapore has become the first Asian country to mandate climate disclosures for non-listed companies, the UK plans economy-wide requirements, and Nigeria's roadmap includes SME reporting by 2030 (S&P Global, 2026). However, private firms remain largely exempt in most countries, including the United States. This regulatory focus rests on an implicit assumption that large public firms face the most material climate risks and that investors in these firms need climate information for capital allocation decisions. Yet public firms represent only 0.1% of U.S. businesses.

[1] The Commission received over 10,500 comments via form letters, another 3,200 comments from individuals, and over 900 comments from companies, NGOs, trade associations, and other organizations (Lee and Smith, 2022).

[2] State Attorney Generals' comment letter on SEC's Climate Risk Disclosure Proposal (see `https://www.sec.gov/comments/climate-disclosure/cll12-8915606-244835.pdf`).

Private firms account for the remaining 99.9%, generate 44% of economic activity, and employ over 56 million workers (SBA, 2019; The White House, 2023). Despite their economic importance, private firms are excluded from U.S. climate disclosure requirements and remain largely invisible in policy discussions about climate risk.

Hurricane Ian illustrated this gap in September 2022. The storm caused an estimated $112 billion in damages, making it the costliest hurricane in Florida history (National Hurricane Center, 2023). Large publicly traded companies with diversified operations recovered quickly, while small businesses required substantial federal support, with the SBA approving over $1 billion in disaster loans within two months of the storm (SBA, 2022). Because private firms file no public financial statements, their losses remained invisible to investors, regulators, and researchers.

We ask whether this pattern generalizes. Do climate disasters affect public and private firms differentially? If public firms are resilient while private firms are vulnerable, current disclosure mandates may not capture the most material climate exposures, leaving an information gap for investors in private firms. Understanding where climate costs actually fall is essential for standard setters designing disclosure requirements and for policymakers allocating regulatory resources toward the most material exposures.

Theory suggests several channels through which climate disasters may affect firm performance. Physical disruption is the most direct: disasters damage buildings, equipment, and inventory, forcing closures (Ponticelli et al., 2023). Demand may shift as local customers face financial distress, particularly for firms serving discretionary rather than essential needs (Pan et al., 2020). Financial constraints may amplify these shocks, as firms lacking cash reserves cannot bridge temporary revenue shortfalls (Giroud and Mueller, 2017).

However, these effects likely vary across firm types. Public firms possess structural advantages that may provide resilience: they operate across multiple locations, enabling reallocation when individual sites are impaired (Acharya et al., 2022; Castro-Vincenzi, 2024), and they maintain greater financial resources to absorb temporary disruptions (Dinlersoz et al., 2024). Private firms lack these advantages. They concentrate operations in single locations (94% in our sample operate in a single county) and face well-documented constraints in accessing external finance (Saunders and Steffen, 2011). These structural differences suggest private firms may experience larger and more persistent effects from climate disasters than public firms.

We test these predictions and provide the first large-scale evidence on how climate disasters affect public and private firm operating performance. We use establishment-level data from Infogroup, which provides comprehensive coverage of U.S. business establishments with detailed information on location, sales, employment, and industry classification. We match these establishments to FEMA (Federal Emergency Management Agency) records covering approximately 2,100 climate-related natural disasters declared between 1953 and 2022. Because our Infogroup data begin in 1997, our analysis covers the period 1998–2022. After aggregating sales to the firm-county-industry-year level, our regression sample contains approximately 30 million observations, each representing a parent firm's local operations in a given county and industry in a given year. The sample includes 26.9 million observations for private firms and 3.3 million for public firms.

Our identification strategy exploits geographic variation in disaster exposure, implementing a difference-in-differences design that compares sales growth at firms' local operations in disaster-affected counties to those in unaffected counties. We include parent firm fixed effects to absorb time-invariant firm characteristics, county fixed effects to absorb time-invariant local conditions, and year fixed effects to absorb common annual shocks. Identification thus comes from within-firm, within-county variation in disaster exposure over time.

Our analysis generates three main findings. First, we document a striking divergence between public and private firm responses to climate disasters. Public firms show no significant operating performance effects at the aggregate level, with sales growth at public firms' local operations in disaster-affected counties statistically indistinguishable from operations in unaffected counties. Private firms, in contrast, experience significant contemporaneous sales declines of 0.7% on average at local operations in disaster-affected counties, measured at the firm-county-industry-year level. For the median private firm-county-industry-year observation with approximately \$500,000 in annual sales, this translates to roughly \$3,500 in lost revenue per disaster.[3] To gauge aggregate

[3]We approximate median private firm revenue using the U.S. Census Annual Business Survey 2023. The median

magnitude, we estimate that climate disasters cause approximately $1 billion in annual sales losses across the private sector, based on the average number of establishments affected by disasters each year and our estimated effect sizes. Event-study analyses confirm parallel trends in the years preceding disaster exposure, supporting our difference-in-differences identification. These declines persist in specific industries. Manufacturing and consumer durables show significant negative effects in each of the four post-disaster years we examine, indicating that climate shocks cause lasting operational disruptions rather than transient effects in industries with location-specific assets and capital-intensive production.

Second, we identify mechanisms that can partially explain the public–private differential. Geographic concentration accounts for an important part of the difference. Private firms operating in a single state experience sales declines of 0.8% following disasters, compared to a statistically insignificant 0.1% for geographically diversified private firms and no effect for public firms. The underlying concentration is even more pronounced at the county level. 94% of private firms in our sample operate in a single county, leaving them exposed to local disaster shocks while multi-location firms can reallocate production and resources across geographically distinct establishments. Access to credit also partially explains the differential. In counties receiving SBA disaster loans, private firm sales do not decline on average, compared to a decline of 1.7% in counties without such assistance. We find corroborating evidence using local bank coverage. Private firms in counties with greater bank presence experience attenuated disaster effects, consistent with local credit access mitigating disaster impacts.

Third, we document substantial industry heterogeneity that is far more pronounced for private firms than for public firms. Among private firms, manufacturing, retail, chemicals, and healthcare experience significant sales declines ranging from approximately 1.0% to 4.1%. These industries share characteristics that limit firm-level adaptation. Manufacturing and chemicals rely on location-specific physical capital and specialized supply chains. Retail and healthcare deliver goods and services to local customers in physical facilities. For these industries, neither geographic diversification nor access to credit fully offsets disaster impacts. Other industries, including

employer firm falls within the $500,000–$999,999 sales bin. We conservatively use the lower bound (i.e., $500,000). This figure is an approximation, as our regression sample may differ from the Census distribution.

consumer nondurables, telecommunications, business equipment, and finance, show neutral or positive effects, consistent with demand shifts toward essential goods and services during disasters. Public firms show no significant effects in most industries. The exceptions are healthcare, where public firms also experience a decline of 1.3%, indicating that even diversified healthcare operators face disaster impacts where services cannot easily be delivered elsewhere, and finance, where public firms experience a small positive effect of 0.8%, likely reflecting demand for financial services in disaster aftermath. These industry-level patterns suggest that climate disclosure standards may benefit from industry-tailored approaches.

Our paper makes three contributions. First, we provide the first systematic comparison of public and private firm climate exposure, which fills a critical gap in the literature. Prior research examines exclusively public firms and finds heterogeneous results across settings. Addoum et al. (2020) find no temperature effects on sales. Addoum et al. (2023) find effects in 24 of 59 industries. Huynh and Xia (2021) find market overreaction then reversal. Pankratz et al. (2023) find heat reduces operating income internationally. We complement this literature by showing that for acute physical disasters, public firms are largely resilient, while the largest effects fall on private firms that have been absent from prior research. We use Infogroup's establishment-level data to provide the first large-scale evidence on how private firms respond to climate disasters.

Second, we identify the mechanisms behind the public–private differential and the conditions under which these mechanisms may fail. Geographic diversification and access to credit each attenuate disaster effects for private firms in aggregate, consistent with these mechanisms playing a role in firm-level adaptation. Neither mechanism, however, protects firms in capital-intensive industries that cannot easily relocate production. Diversified private manufacturing firms experience disaster declines indistinguishable from concentrated firms, and local banking presence does not attenuate effects in manufacturing or healthcare. This pattern suggests that disaster vulnerability in some industries reflects features of production technology that firm-level choices about diversification or financing cannot easily address. The contribution is to move beyond documenting differential exposure to identifying the boundary conditions of the mechanisms that produce it.

Third, our findings directly inform the ongoing international debate about the scope of climate disclosure requirements. The SEC's rules, like ISSB standards adopted in over 30 jurisdictions, require public firms to disclose material climate risks, premised on the assumption that these firms face significant exposure. Our evidence challenges this assumption. Public firms show no aggregate effects from climate disasters, supported by geographic diversification and access to financial resources. The firms most affected by climate disasters are private firms that are small and geographically concentrated, precisely those excluded from disclosure requirements. This creates a gap between where standardized climate risk information exists and where climate costs actually fall. As jurisdictions including Singapore, the UK, and Nigeria consider extending disclosure requirements to private firms, our evidence provides empirical grounding for these policy decisions by documenting where climate costs actually fall. Investors in private firms, including banks, private equity funds, and the SBA, lack standardized climate risk information precisely for the firms most vulnerable to climate shocks.

Our focus on acute physical disasters complements research on chronic climate variables such as temperature. While temperature studies examine adaptation to shifting climate norms, we examine resilience to sudden operational disruption. The SEC's rules and ISSB standards recognize both dimensions, requiring disclosure of "severe weather events such as hurricanes and floods" (acute, our focus) and "chronic changes such as higher average temperatures" (chronic, prior work).

2 Related Literature and Institutional Background

2.1 FEMA Disaster Declarations

The Federal Emergency Management Agency (FEMA) declares disasters when state governors request federal assistance for events exceeding local response capacity. These declarations trigger federal aid including SBA disaster loans, FEMA grants, and infrastructure assistance, making them economically meaningful events for affected communities. Figure 1 shows that declarations have increased substantially over time, from an average of 27 per year in the 1990s to 47 per year in the 2010s, reflecting both increased climate volatility and greater awareness of federal assistance programs.

We use FEMA declarations as our measure of climate disaster exposure for three reasons. First, declarations provide consistent geographic coding at the county level and precise event timing across the full FEMA record (1953–2022), which allows us to conduct systematic analysis. Our Infogroup data begin in 1997, so our analysis covers 1998–2022, capturing over 2,100 climate-related disasters. Second, declarations represent events of sufficient severity to warrant federal intervention, filtering out minor weather events unlikely to affect firm operations. This severity threshold aligns with the SEC's climate disclosure rules, which require firms to disclose "severe weather events such as hurricanes, tornadoes, flooding, and wildfires" that may have material impacts. Third, unlike insurance claims or damage estimates available only for recent decades, FEMA declarations provide consistent definitions throughout our sample period.

One potential concern is that FEMA declarations may be subject to political influence, as governors must request declarations and the president has discretion to approve them (Reeves, 2011). We address this concern in three ways. First, in untabulated analyses, we demonstrate that FEMA declarations strongly correlate with objective measures of disaster severity from NOAA (correlation = 40%). This correlation, while not perfect, indicates that declarations capture genuine disaster events rather than purely political considerations. Second, our results are robust to excluding disasters declared in presidential election years, when political motivations might be strongest (untabulated). Third, our specifications include county fixed effects, which absorb any time-invariant political factors, such as a county's typical propensity to receive declarations, that might influence declaration likelihood.

2.2 Conceptual Framework

Having established our measure of disaster exposure, we now develop a framework for understanding how disasters affect firm performance and why effects may differ between public and private firms. Our framework synthesizes insights from recent work on temperature shocks and manufacturing productivity (Ponticelli et al., 2023), demand shifts during disasters (Pan et al., 2020), and financial frictions in disaster contexts (Benincasa et al., 2024).

2.2.1 How climate disasters affect firm performance

Consider a firm with establishments in one or more geographic locations. When a severe weather event strikes, firms experience several interconnected shocks. First, physical damage destroys or impairs buildings, equipment, inventory, and other tangible assets. Unlike planned depreciation, disaster losses are sudden and require immediate cash for repair or replacement. Insurance coverage, when present, rarely covers full replacement costs or business interruption losses (Klomp, 2014).

Second, disasters create local demand shocks. For firms selling to local consumers, regional income declines reduce sales directly. However, demand effects are not uniformly negative. Pan et al. (2020) show that consumers engage in pre-disaster stockpiling behavior, particularly for food, water, and emergency supplies, leading to temporary demand spikes for certain product categories. Grocery stores, pharmacies, telecommunications providers, and repair services often see demand increases, while discretionary purchases decline sharply (Liu and Strahilevitz, 2025).

Third, the combination of lost revenue, fixed costs, and unexpected emergency expenses creates intense financial pressure. Firms must cover unanticipated repair costs and temporary facilities while revenues decline. This cash flow squeeze forces firms to seek external financing when lenders are most cautious. Benincasa et al. (2024) find that firms suffering weather-related losses tend to be more leveraged afterward, suggesting that disasters contribute to balance sheet erosion. Firms unable to obtain credit may be forced to scale back operations or shut down entirely, which is a particular concern for small businesses that lack financial buffers (Huynh et al., 2020).

2.2.2 Why Public and Private Firms May Differ in Climate Resilience

These shocks affect all firms exposed to disasters, but the magnitude and persistence of impacts likely vary across firm types. Public and private firms differ along three dimensions that shape disaster vulnerability.

First, public and private firms differ in access to financial resources. Public firms can draw on credit lines with major banks, access commercial paper markets, and issue equity. Their transparent financial reporting reduces information asymmetry, making lenders willing to extend credit on favorable terms. Dinlersoz et al. (2024) show that public firms maintain larger cash reserves relative to assets, providing self-insurance against temporary shocks. In contrast, private firms typically rely on relationship banking with local banks and have limited capital market access (Pagano et al., 1998). Saunders and Steffen (2011) document that private firms pay substantially higher interest rates, with spreads widening during economic stress. During disasters, when lenders become risk-averse and local banks may themselves be impaired, these disadvantages intensify.

Second, public and private firms differ in geographic diversification. A firm operating across many locations has a natural hedge against localized disasters. When floods close facilities in one region, the firm can shift production to unaffected locations, reallocate inventory, or redirect customer service to functioning offices. Castro-Vincenzi (2024) shows that large firms in the automobile industry can partly absorb weather shocks by reallocating production from affected to unaffected plants. Acharya et al. (2022) demonstrate that multi-location firms are more resilient to heat shocks than single-location firms. Public firms tend to operate across many counties and states, while private firms typically operate in a single location.

Third, public and private firms differ in external support. Comprehensive business interruption insurance can reduce disaster impacts, but private firms are less likely to maintain such coverage due to higher premiums and cash flow constraints (Klomp, 2014). Government disaster assistance through SBA loans provides support that private firms often qualify for and use, while public firms are largely ineligible due to size thresholds and rarely need such assistance.

Beyond these firm-level differences, disaster impacts vary across industries. Industries producing essential goods experience neutral or positive demand shocks as consumption shifts toward necessities, while discretionary industries see declines as consumers postpone purchases. Industries with high physical capital intensity suffer more from asset damage than service industries (Ponticelli et al., 2023). Industries relying on complex, specialized supply chains face greater disruption than those with generic, easily substitutable inputs (Castro-Vincenzi, 2024).

Based on this framework, we develop four predictions.

H1 (Public-Private Differential): Private firms experience larger operational disruptions from climate disasters than public firms.

H2 (Geographic Diversification): Geographic diversification attenuates disaster effects. Because private firms are typically less diversified than public firms, this mechanism partially explains the public-private differential.

H3 (Access to Credit): Access to credit attenuates disaster effects for private firms. Both government disaster assistance (SBA loans) and local banking presence may serve this role, with local banking reflecting broader local credit access including relationship lending.

H4 (Industry Heterogeneity): Disaster effects vary across industries based on the substitutability of local operations and the location specificity of productive assets.

3 Data and Variable Construction

3.1 Climate-Related Natural Disasters (CND) Data

We use FEMA's classification of major disasters to identify disasters likely to have significant, material impacts on businesses. FEMA declares a major disaster after a state's governor or tribal leader requests federal assistance for an incident that exceeds local and state response capabilities. This declaration is based on an assessment of the disaster's severity, scope, and financial strain on affected communities.[4]

We compile a county-level record of all climate-related natural disasters (CND) occurring between May 1953 and May 2023, sourced from the "Disaster Declarations Summaries" file provided by OpenFEMA Data Sets.[5] This dataset, obtained directly from OpenFEMA, lists all official FEMA Disaster Declarations since 1953 and includes three types of events labeled as (i) major disaster, (ii) emergency, and (iii) fire management assistance. The dataset lists the type of disaster event, the start and end date of the disaster, and the Federal Information Processing Standards (FIPS) code of affected states and counties. We specifically focus on natural disasters that are more likely to be impacted by climate change and exclude man-made disasters, as well as natural disasters unlikely to be impacted by climate change, such as earthquakes and volcanic eruptions.[6]

[4] Once the President of the United States approves the request, the declaration grants access to federal resources and funding to support recovery efforts, including individual assistance, public infrastructure aid, and hazard mitigation. See `https://www.fema.gov/disaster/how-declared`.

[5] `https://www.fema.gov/about/openfema/data-sets#disaster`.

[6] We include the following disasters in our CND definition: drought, fire, flood, tropical storm (including hurricane and typhoon), winter storm (including snowstorm and severe ice storm), and coastal storm.

Our final sample includes approximately 2,100 climate-related disasters. Because our Infogroup data begin in 1997, our analysis covers 1998–2022.

FEMA declarations offer three advantages for studying climate impacts on firms. First, declarations provide objective materiality thresholds: if FEMA declares a disaster, damage is severe enough to exceed state and local response capacity. This contrasts with temperature studies where researchers must specify what constitutes "extreme" exposure. Second, declarations provide precise treatment timing at the county level, which allows us to implement a clean difference-in-differences identification. Third, declarations trigger observable policy responses (SBA loans, FEMA aid) whose effectiveness we can evaluate. These features complement prior research examining chronic climate variables such as temperature (Addoum et al., 2020, 2023), heat exposure (Pankratz et al., 2023), and drought (Hong et al., 2019). While temperature studies examine whether firms adapt to shifting climate norms, we examine whether firms can withstand acute physical shocks. The SEC's 2024 climate rule recognizes both dimensions, requiring disclosure of "severe weather events such as hurricanes and floods" (our focus) and "chronic changes such as higher average temperatures" (temperature studies' focus).

We discuss several caveats and limitations. First, FEMA declarations may reflect political considerations, as governors must request declarations and presidents have approval discretion (Garrett and Sobel, 2003; Reeves, 2011). We address this concern by including county fixed effects, which absorb time-invariant political characteristics, and by verifying that FEMA declarations correlate with objective NOAA severity measures (correlation = 0.40). Results are also robust to excluding disasters declared in presidential election years (untabulated). Second, FEMA declarations may miss localized events that affect specific firms but fall below federal assistance thresholds. This omission likely biases our estimates toward zero, which makes our findings conservative. Third, firms may select locations based on climate risk, inducing correlation between disaster exposure and unobserved characteristics. We address this through firm and county fixed effects, and through matched sample robustness checks.

3.2 Firms' Establishment Data

We identify where firm establishments are physically located as well as sales volume at these locations using Infogroup data. Infogroup reports the branches and headquarters of both public and private firms in the U.S. This dataset has been widely used in prior literature (e.g., Liu and Lu, 2023). Infogroup compiles information such as business identification, location, industry, number of employees, and sales volume data for each business unit. Each business unit can be categorized as either the headquarters or a branch, with branches representing all affiliated locations of a firm, including retail storefronts, regional offices, plants, and subsidiaries. The data are collected from various public sources, such as the yellow pages and credit card billing statements. Infogroup also provides detailed employee counts and sales volume for each business location. Its aggregate zip-code level employee count exhibits a 92% correlation with data from the 2018 Census Bureau's County Business Patterns. This correlation indicates the reliability and comprehensiveness of Infogroup data.

However, the number of employees and sales data might not be updated frequently. This issue is likely to be more pronounced for private companies, where there is a lack of public disclosure and alternative information sources, such as financial statements or analyst reports. To alleviate these potential data issues, we scrub the data by removing samples with a higher probability of errors. We first eliminate all branches without sales or employee data, as well as those firms listed with zero sales or zero employees.[7] We then exclude observations where there is no change in sales over a specified period, as this lack of variation may indicate data entry errors or other anomalies based on our random sample checking.

Additionally, the Infogroup database focuses on registered business locations rather than providing a comprehensive inventory of firms' physical assets. As such, it may not capture distributed infrastructure, such as agricultural fields, that are spatially separate from the listed business site. This limitation may be more pronounced for asset-intensive industries where climate exposure is not confined to a single location. However, because our empirical focus is on financial

[7] Excluding branches without sales or employee data may underrepresent some climate-vulnerable assets. However, retaining these observations would add noise without analytical value given the absence of alternative activity measures.

outcomes associated with reported business activity, disruptions at primary business locations still provide a meaningful proxy for operational exposure to severe weather. To the extent that off-site asset impacts go unrecorded, this limitation would likely attenuate the estimated effects, leading to more conservative inferences.

We use a two-stage process to identify publicly traded firms. First, we use ticker information provided by Infogroup. A business entity is classified as public if either its parent company or any subsidiary has a ticker symbol in Infogroup. We match names for the remaining entities in our sample to pair them with firms in the Compustat database. A business entity is coded as public if the business unit shares an exact name match with a publicly listed firm in the Compustat database. The remaining eligible firms are designated as private firms.

3.3 Descriptive Statistics

We use two units of analysis in this paper. The regression sample is at the firm-county-industry-year level, capturing each parent firm's local operations in a given county and industry. The first four variables in Table 1 (*Change_Sales*, *Disaster_d*, *Sales*, and *Num of Employees*) are reported at this level. Remaining descriptive statistics about firm-wide geographic exposure (such as the number of counties in which a firm operates) are computed at the parent-firm-year level. The distinction matters because diversification is a firm-level characteristic, while disaster impact is measured at the level of local operations.

Panels A and B of Table 1 provide descriptive Infogroup sample statistics for public and private firms. Our sample period starts in 1998 as the Infogroup data begin in 1997. On average, private firms are slightly more likely to be exposed to disasters (26% of the total sample) than public firms (24%). We have 3,293,611 (26,884,761) firm-county-industry-year observations (i.e., parent-firm-county-industry cells per year, representing each firm's local operations) for public (private) firms across 13,513 (8,924,732) unique parent firms. This statistic indicates that public firms are more dispersed geographically than private firms. The local operations of an average public firm are larger than those of an average private firm in terms of both sales volume ($23.7 million versus $2.6 million) and number of employees (181 versus 11). Public firms are also more diversified than private firms. A median public firm has business units in over 400 counties across 46 states,[8] whereas the operations of most private firms in our sample are concentrated in a single state. Consistent with this, when a disaster occurs, only about 4% of a public firm's total sales is exposed to that event, compared to 94% for the average private firm. Therefore, these summary statistics suggest that public firms are more likely to recover faster from a CND event at one of their locations using support from their remaining business units. On the other hand, private firms might not have such options available to them.

4 Findings

4.1 Baseline Results: Public Versus Private Firm Operating Performance

4.1.1 Main Results

We begin by testing our central hypothesis that private firms experience larger operating performance effects from climate disasters than public firms. As developed in Section 2, public firms possess structural advantages, including geographic diversification and financial resources, that may provide resilience to localized shocks. We test whether these advantages translate into differential disaster impacts.

To measure the impact of climate and natural disasters on operating performance, we match establishment-level data from Infogroup with the FEMA CND database based on county FIPS codes, then aggregate sales to the firm-county-industry-year level. The dependent variable, $Sales_{i,t,l,j}$, represents the total sales of parent firm i in year t in county l in industry j, summed across all establishments (subsidiaries) of firm i in that county-industry combination. We refer to this unit of analysis as the firm's "local operations" throughout the paper, and the unit of observation in our regression is the firm-county-industry-year. Appendix B provides a simplified example of this construction. Sales growth, our outcome variable, is computed as

$$Change\_Sales_{i,t,l,j} = \frac{Sales_{i,t,l,j} - Sales_{i,t-1,l,j}}{Sales_{i,t-1,l,j}}.$$

[8] These geographic diversification statistics are computed at the parent-firm-year level, counting unique counties and states in which each parent firm has at least one establishment in operation that year, and are distinct from the firm-county-industry-year unit used in our regressions.

We estimate the following regression separately for public and private firms, first on the full sample to obtain average effects and then separately within each of the Fama-French 12 industries to examine industry heterogeneity:

$$Change\_Sales_{i,t,l,j} = \alpha + \beta\, Disaster\_d_{l,t} + \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}, \quad (1)$$

We measure exposure to CND using an indicator variable, $Disaster\_d_{l,t}$, equal to one if county l experienced any CND in year t and zero otherwise. Because the disaster indicator is defined at the county-year level, it is constant across all firm-industry observations within a given county-year. While the disaster treatment varies at the county-year level, the outcome (sales growth) varies at the firm-county-industry-year level, allowing us to identify how disaster effects differ across firm types and industries. Our inference accounts for this dependence structure through firm-level clustering, discussed below.

We aggregate sales to the firm-county-industry-year level rather than to firm-year or county-year for two reasons. First, retaining the firm dimension is essential for our public–private comparison, which requires firm-level identification. Second, retaining the county and industry dimensions allows us to measure disaster impacts at the geographic level where disasters occur and to examine industry heterogeneity in firm responses. Aggregating to higher levels (e.g., firm-year) would dilute disaster exposure for geographically diversified firms, which could obscure the diversification mechanism we study. Public and private firms are aggregated using the same rule so that the public–private comparison is not confounded by differences in aggregation.

Our specification uses three sets of fixed effects to address potential confounders. Parent firm fixed effects absorb time-invariant firm characteristics, both observed and unobserved, that may correlate with both disaster exposure and operating performance. County fixed effects absorb time-invariant differences across counties, including baseline political environment and disaster preparedness. Year fixed effects absorb common annual shocks, including national political cycles such as changes in disaster declaration behavior during presidential election years (Reeves, 2011). We do not include industry fixed effects because our main analyses are conducted separately within each of the Fama-French 12 industries. The industry-specific subsamples isolate within-industry variation by construction, so industry fixed effects would be redundant. Together, these fixed effects mean that identification comes from comparing sales growth at firms' local operations in disaster-affected counties to sales growth at firms' local operations in unaffected counties within the same year, after absorbing time-invariant parent firm characteristics (parent firm fixed effects), time-invariant county characteristics (county fixed effects), and common annual shocks (year fixed effects).

We cluster standard errors at the parent firm level to account for within-firm correlation across the firm's multiple local operations (firm-county-industry cells) and over time. Each parent firm appears in our sample many times within a year (across different county-industry combinations) and across years, so within-firm correlation is the dominant dependence structure relevant to our inference. While disaster exposure varies at the county-year level, firms make operating, financing, and risk management decisions at the organizational level.

A key identification challenge is endogenous location choice: firms select locations based on climate risk, labor costs, and market access, potentially inducing correlation between disaster exposure and unobserved firm characteristics. FEMA disasters mitigate this concern in two ways. First, conditional on location, disaster occurrence in any given year is plausibly exogenous. A firm in Miami chose to locate there knowing long-run hurricane risk, but cannot predict whether a hurricane will strike in 2024. Second, our fixed effects structure absorbs selection. County fixed effects absorb time-invariant climate risk (Florida is hurricane-prone). Firm fixed effects absorb time-invariant firm characteristics (some firms are better prepared).

To validate our identification strategy, we examine parallel trends in an event-study framework. Because our setting features staggered treatment timing across counties, recent work has shown that two-way fixed-effects estimators can yield biased estimates when treatment effects are heterogeneous over time or across units (De Chaisemartin and d'Haultfoeuille, 2020; Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Goodman-Bacon, 2021). We address this concern by restricting the event-study sample to first-time disaster exposure for each firm-county pair with clean pre- and post-event windows, which avoids contamination from already-treated comparison units. We focus on first-time disaster exposure for each firm-county pair, requiring four clean pre-event years and two clean post-event years (no other disasters in the window). Figure 2 plots the coefficients on event-time indicators. The pre-trend coefficients are small and statistically indistinguishable from zero, supporting the parallel trends assumption. The effect emerges at $t = 1$ and persists in subsequent periods.[9]

Table 2 reports the results from estimating Equation (1) for each industry separately for public and private firms. On average, the coefficient on $Disaster\_d$ is statistically insignificant for public firms in column (2). In contrast, the coefficient on $Disaster\_d$ is negative and statistically significant for private companies in column (4). To contextualize the magnitude, the estimated 0.7 percentage point decline represents the average reduction in sales growth at the firm-county-industry-year level (i.e., the average reduction in growth at a firm's local operations in a disaster-affected county) and corresponds to approximately 5.8% of mean sales growth for private firms (12 percentage points). The economic magnitude varies across industries, with manufacturing and retail experiencing larger proportional effects.

At the industry level, we find heterogeneous impacts of CND on sales growth. Private firms in manufacturing, chemicals, retail, and healthcare experience statistically significant sales declines when hit by a CND (coefficients of -2.1%, -1.8%, -1.0%, and -4.1%, respectively). Private firms in consumer nondurables, business equipment, telecom, finance, and other industries experience statistically significant sales increases. Energy shows a positive coefficient that is marginally significant ($p < 0.10$). Utilities and consumer durables show no statistically significant effects.[10]

The results indicate that sectors catering to essential goods, such as telecom (e.g., communication services) and consumer nondurables (e.g., perishable food), experience significant sales increases following CND. Previous studies and news coverage discuss how demand for essential goods (specifically consumer nondurables) increases in anticipation of disaster and could lead to

[9] Our event-study analysis focuses on first-time disaster exposures for each county, where identification is cleanest. Counties experiencing repeated disasters may exhibit more complex dynamics reflecting both new shocks and recovery from prior events.

[10] We further find that the coefficient on $Disaster\_d$ turns negative and statistically significant for Consumer Durables and Energy sectors after accounting for financial assistance provided by the SBA. This result suggests that the initially observed positive coefficient of $Disaster\_d$ in Table 2 may partially reflect the positive impact of the financial aid.

stockpiling (Pan et al., 2020). Energy firms show marginally significant positive effects, potentially reflecting increased demand for fuel during extreme temperature fluctuations accompanying certain CND events (Schwan, 2024; Sensix, 2023).

On the other hand, sectors producing goods whose consumption could be postponed, such as manufacturing (e.g., machinery and trucks) and shops (e.g., retail stores), experience statistically significant sales declines following CND. We also document a significant decline in sales for private firms in the healthcare industry following CND events, likely reflecting both reduced demand for elective services and disruption to healthcare facilities, staffing, and supply chains.

Overall, the results suggest that private firms are significantly affected by CND across industries, while public firms show no significant effects in most industries. The exceptions are healthcare, where public firms experience a significant decline of 1.3%, consistent with the local nature of healthcare delivery where even diversified operators cannot easily redirect care to facilities in unaffected counties, and finance, where public firms experience a significant positive effect of 0.8%, likely reflecting increased demand for insurance claims processing, recovery loans, and disaster-related financial services. We focus subsequent analysis on the aggregate public–private comparison while noting these industry-specific exceptions.

A natural concern is that firm size alone drives our results. Private firms are substantially smaller than public firms in our sample (Table 1). If size fully explains the public–private differential, comparing private firms to similarly sized public firms should eliminate the difference in disaster impacts. To test this, we use propensity score matching (PSM) to construct a size-matched sample.[11] We match each private firm to three public firm nearest neighbors based on the natural log of sales and the natural log of employees in the year before the disaster. Results using the matched sample (Online Appendix Table OA2) indicate that size alone does not explain our findings. Private firms continue to experience significant sales declines following disasters, while matched public firms of similar size show no significant effects. These results suggest that organizational form matters beyond what size alone can explain.

[11] In untabulated tests, we also check robustness using the nearest-neighbor match specification. The results are qualitatively similar.

Overall, the results in Table 2 suggest that private firms affected by CND are significantly more likely to suffer adverse impacts.[12] However, there is no significant difference in the sales performance of public firms regardless of their exposure to CND.

4.1.2 Robustness Tests

We conduct four robustness tests to validate our main findings, organized by the concern each addresses. First, to ensure results are not driven by extreme values or data quality issues, we confirm that findings hold when restricting the sample to observations with absolute sales growth below 100% or 200%. Results are also insensitive to the rule used to drop potentially stale observations. We obtain similar findings whether we exclude observations with no sales change over two, three, or four consecutive years. Second, to address concerns that county characteristics confound disaster exposure, we augment our baseline specification with annual county-level controls, including GDP, total establishment count, employment levels, and payroll. Results for private firms remain robust across all industries.

Third, we address potential state-level confounds. We do not include state $\times$ year fixed effects because many severe disasters affect entire states. Smaller states such as Rhode Island (with only five counties) experience most disasters at the state level, so state $\times$ year fixed effects would absorb the disaster variation we seek to identify and bias estimates toward zero. Instead, we control for time-varying state-level conditions along three dimensions. For economic conditions, we add state GDP.[13] For chronic climate exposure, we add Cooling Degree Days and Heating Degree Days to proxy for temperature effects documented in prior work (Addoum et al., 2020, 2023). For the political environment, we add indicators for Democratic control of the governor, state legislature, and overall state government, given evidence that disaster declarations may reflect political considerations (Reeves, 2011). Results remain robust across all these specifications.

Finally, to assess potential survivorship bias, we examine firm exit rates following disasters. We define exit in three ways: (1) firm-county-industry exit, where the firm's local operations in a

[12] Because we lack cost and profit data for private firms, we cannot assess supply-side shocks such as production disruptions. Our estimates therefore represent a lower bound on the direct damage firms experience from climate disasters.

[13] County-level and state-level economic controls are measured at $t-1$ to avoid contemporaneous correlation with the dependent variable.

given county-industry cell disappear in the subsequent year; (2) firm-county exit, where the firm has no operations in that county in the subsequent year, across any industry; and (3) firm exit, where the firm has no operations anywhere in the subsequent year. For each definition, we compare exit rates for firm-county-industry observations in disaster-affected versus unaffected county-years. Exit rates are slightly higher for disaster-affected private firms (18–19%) compared to unaffected firms (17–18%), a difference of approximately one percentage point. While this difference is modest, it implies that our estimates may understate the true impact of disasters to the extent that the most severely affected local operations exit the sample. We therefore interpret our findings as lower bounds on disaster effects.

4.2 Mechanisms

Having documented that private firms experience larger disaster effects than public firms, we next examine mechanisms underlying this differential. Our conceptual framework identifies two key factors: geographic diversification, which enables firms to reallocate resources across unaffected locations, and government financial assistance, which provides liquidity to constrained firms.

4.2.1 Diversification

We first investigate how the correlation between CND and sales varies across firms based on their geographical diversification. The idea behind this test lies in the differential reliance of firms on local demand. Firms operating across multiple geographies typically depend less heavily on the local market than those concentrated (Acharya et al., 2022; Addoum et al., 2023). By assessing the impact of CND on both diversified and non-diversified firms, we study how the differential dependence of firms on local consumer demand may influence their responses. To this end, we partition our sample into two groups based on geographical diversification at the state level. For every firm-year pair, we compute the number of states in which a firm has establishments. We divide our sample into two subsamples: *Concentrated* if the firm is only present in one state and *Diversified* if the firm is in more than one state.

Panel A of Table 3 presents the results for private firms. For geographically concentrated firms, the aggregate disaster effect is negative and statistically significant (-0.8%, $p < 0.01$). For geographically diversified firms, the aggregate effect is statistically insignificant (0.1%, $p > 0.10$), consistent with diversification attenuating disaster impacts. At the industry level for concentrated firms, manufacturing (-2.1%), chemicals (-2.2%), retail (-1.1%), and healthcare (-4.2%) experience statistically significant declines, while consumer nondurables, business equipment, telecom, finance, and energy show positive effects. Among diversified firms, most industries show statistically insignificant disaster effects, consistent with diversification providing protection.

One exception is manufacturing. Diversified manufacturing firms experience disaster effects of -2.2%, statistically indistinguishable from the -2.1% experienced by concentrated firms. Geographic diversification appears not to protect manufacturing firms against disaster impacts. This pattern is consistent with manufacturing operations relying on specialized equipment, tooling, environmental permits, and intermediate-input supply chains that are difficult to substitute across locations, although our analysis does not directly identify which of these factors drives the result. The diversification mechanism appears to operate in industries where production can be relocated more easily and is weaker in industries with substantial physical capital and supply chain dependencies.

Panel B of Table 3 presents the results for public firms. Only 4% of the public firm sample is geographically concentrated. On average, we do not find any impact of CND on public firms. Among geographically concentrated public firms, CND seems to negatively affect only firms in the healthcare and consumer durable sectors. Among geographically diversified firms, only healthcare firms suffer because of CND, while firms in the finance sector seem to benefit after a CND.

Overall, the results suggest that geographically diversified private firms are less impacted than those that are geographically concentrated. Most adverse sales shocks are primarily experienced by firms operating in concentrated states, and geographic diversification appears to contribute to the resilience of public firms to CND.

4.2.2 Financial Assistance and Access to Credit

We next investigate whether access to credit attenuates the impact of CND on private firms. Financial constraints amplify disaster impacts by preventing firms from financing repairs and bridging revenue shortfalls. We examine two channels: government disaster assistance through SBA loans and private credit access through local banking relationships.

Government Financial Assistance. SBA disaster loans directly address this constraint by providing low-interest credit to affected small businesses. If liquidity constraints are a key mechanism underlying private firm vulnerability, we would expect disasters to have smaller effects in counties receiving SBA assistance. To test this, we modify the specification in Equation (1) as follows:

$$\begin{aligned} Change\_Sales_{i,t,l,j} = \alpha + \beta_1\, Disaster\_d_{l,t} \times SBA\_d_{l,t} + \beta_2\, Disaster\_d_{l,t} \\ + \beta_3\, SBA\_d_{l,t} + \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}, \end{aligned} \tag{2}$$

where $SBA\_d_{l,t}$ is an indicator variable that equals one if county l has received government financial assistance in year t, and zero otherwise.[14] The coefficient on $Disaster\_d \times SBA\_d$ captures whether disaster effects on local sales growth differ in counties that received SBA disaster assistance. We use the Disaster Loan dataset maintained by the SBA, which reports loan amounts approved in each county for affected small businesses.[15] Because the dataset is available only for fiscal years 2000–2003 and 2008–2022, we exclude observations from 1998–1999 and 2004–2007, which reduces the estimation sample for this test. The remaining empirical specification is the same as in Equation (1).

Panel A of Table 4 reports results from estimating Equation (2) separately for each industry within private firms. The coefficient on $Disaster\_d \times SBA\_d$ is positive and statistically significant on average, indicating that government financial assistance attenuates the negative impact of disasters on private firm sales. At the industry level, this interaction coefficient is positive and statistically significant for nine out of 12 industries. Financial assistance appears to have a negative incremental impact only in the finance industry.[16]

We interpret these results with caution. SBA disaster loan availability is not randomly

[14]SBA disaster loans are not always disbursed in the same year as the disaster declaration. Loan approvals and disbursements can extend into subsequent years ($t + 1$ or $t + 2$), meaning a county may receive SBA assistance in a year with no active disaster declaration. As a result, a county may show $SBA\_d = 1$ and $Disaster\_d = 0$ in the same year, simply reflecting delayed disbursement for a prior disaster. This independent variation between SBA_d and $Disaster\_d$ is what allows us to separately identify the coefficient on SBA_d in Equation (2).

[15]The data are publicly available at `https://data.sba.gov/dataset/disaster-loan-data`.

[16]In Panel A of Online Appendix Table OA3, we do not find a significant association between government financial assistance and CND's effect on performance for the majority of public firms, likely because SBA disaster loans target small businesses (which are predominantly private), leaving public firms largely outside the scope of this support.

assigned, as counties receiving assistance may differ systematically from those that do not. Disaster severity likely drives both SBA assistance and firm performance, creating potential confounding. Additionally, selection into applying for loans may correlate with firm characteristics such as financial sophistication or program awareness. If assistance flows disproportionately to harder-hit areas, the positive coefficient on $Disaster\_d \times SBA\_d$ may reflect incomplete controls for disaster severity rather than a causal effect of government aid. Conversely, if more resilient firms are also more likely to obtain SBA assistance, our estimates would understate the true benefit of government aid. We view these results as suggestive rather than causal and turn next to corroborating evidence from local banking relationships, where reverse causality is less of a concern.

Local Banking Relationships. To provide corroborating evidence on the role of credit access, we examine a second channel: local banking relationships. Small businesses rely on personal relationships with local lenders to communicate their creditworthiness and obtain financing during distress (Cortés and Strahan, 2017; Nguyen, 2019). Because relationship lending requires proximity and repeated interaction, information asymmetry between lenders and small firms tends to be higher in areas with fewer banks (Petersen and Rajan, 2002; Berger and Udell, 2002). Importantly, unlike SBA assistance, local bank presence is determined by long-run market conditions rather than disaster response, reducing concerns about reverse causality. We acknowledge that county-level bank presence reflects general financial infrastructure as well as relationship lending, and we therefore interpret this channel as capturing local credit access broadly.

Using FDIC Summary of Deposits data, we construct $Above\_Median\_Bank$, an indicator equal to one if the number of banks in a county equals or exceeds the year-specific median. We modify the specification in Equation (2) by interacting this measure with disaster exposure, allowing the disaster effect to differ between counties with above- and below-median bank presence:

$$\begin{aligned} Change\_Sales_{i,t,l,j} = \alpha &+ \beta_1\, Disaster\_d_{l,t} \times Above\_Median\_Bank_{l,t} + \beta_2\, Disaster\_d_{l,t} \\ &+ \beta_3\, Above\_Median\_Bank_{l,t} \\ &+ \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}. \end{aligned} \tag{3}$$

Panel B of Table 4 reports results from Equation (3) for private firms. In aggregate, the coefficient on $Disaster\_d \times Above\_Median\_Bank$ is positive and statistically significant (+0.022, $p < 0.01$), indicating that greater local bank coverage attenuates disaster impacts for private firms on average.[17] The attenuation is statistically significant in consumer durables, chemicals, business equipment, utilities, retail, finance, and other industries. Manufacturing and healthcare, the two industries with the largest contemporaneous declines in Table 2, do not show statistically significant bank attenuation. This pattern suggests that local credit access does not offset disaster impacts in industries where production cannot easily be relocated. Energy shows a negative interaction (-0.033, $p < 0.05$), but the positive main effect of $Disaster\_d$ for energy private firms (+0.038, $p < 0.01$) indicates that the underlying disaster effect for energy is positive rather than negative, so the pattern does not contradict our main argument about credit access attenuating disaster declines.

Together with the SBA results in Panel A, the local banking analysis supports our broader argument that credit access partially explains the public–private differential. We interpret the local banking results cautiously, as county-level bank presence may reflect general financial infrastructure rather than relationship lending specifically. Nonetheless, the consistency between SBA and local banking results provides triangulation. Unlike SBA loan availability, local bank presence is determined by long-run market conditions rather than disaster response, reducing the reverse causality concern that affects the SBA analysis. The convergence of two analyses strengthens our interpretation that credit access contributes to the public–private differential, while the industry-level patterns identify where this mechanism is sufficient and where additional factors are needed to explain disaster vulnerability.

4.3 Persistence of Effects

We also investigate how long the association between CND and sales persists. The duration of disaster effects has important implications. Temporary disruptions suggest private firms can absorb climate shocks, while persistent effects indicate lasting economic damage that may warrant

[17] Results are robust to using branch counts instead of bank counts, and to scaling both by the county's establishment count ($Bank\_firm\_ratio$ and $Branch\_firm\_ratio$). The aggregate interaction remains positive and significant for private firms under both ratio measures. Additionally, the corresponding results for public firms are reported in Panel B of Online Appendix Table OA3. Consistent with the SBA results, public firms show no economically meaningful average response to local bank presence.

policy intervention.

We examine whether the disaster effects extend beyond the year of impact or whether firms recover quickly. To test the dynamic impact of CND, we estimate the following specification:

$$Change\_Sales_{i,t+k,l,j} = \alpha + \beta_1\, Disaster\_d_{l,t} + \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}, \quad (4)$$

where $Change\_Sales_{i,t+k,l,j}$ represents sales growth at the firm's local operations in the k-th year following the CND, for $k = 2, 3, 4$, and 5. We retain the same fixed effects and clustering structure as in Equation (1). To examine persistence among ongoing local operations, we restrict the sample to firm-county-industry cells that remain in the data for at least $k + 1$ years following each disaster event.

A limitation of this approach is that it captures only firms' local operations that continue to exist. To the extent that the most severely affected firms exit the sample, our estimates provide a lower bound on the true persistence of disaster effects. Nevertheless, this analysis provides insight into how quickly surviving firms recover.

Panels A and B of Table 5 report results for private and public firms, respectively. Among private firms (Panel A), manufacturing and consumer durables exhibit the most persistent negative effects, with disasters depressing sales in each of the four post-disaster years we examine. Manufacturing experiences declines of approximately 0.5% to 1.1% at $k = 2$ through 5, consistent with slow recovery in sectors where rebuilding physical capital and supply chains takes time. Consumer durables show no statistically significant contemporaneous effect in Table 2 but develop significant negative effects in all four post-disaster years (−0.7%, −1.0%, −0.5%, and −1.2% at $k = 2$ through 5, respectively). The delayed pattern in consumer durables is consistent with deferred consumer purchase decisions and inventory drawdown that materialize only in subsequent years.

Utilities show small significant negative coefficients at $k = 4$ (−1.2%) and $k = 5$ (−0.2%), suggesting some lingering effects rather than full recovery. Healthcare shows positive small effects in most post-disaster years following a sharp contemporaneous decline of −4.1% (Table 2), consistent with a recovery pattern, though with a small but significant dip at $k = 3$ (-0.5%). Other industries (shops, consumer nondurables, business equipment, finance) show persistent positive effects in post-disaster years, consistent with demand shifts toward essential goods and services. We focus our discussion on industry-level persistence patterns. The aggregate (All) coefficient in Table 5 is positive because industries with positive demand-driven responses account for a large share of the sample, masking the persistent declines in capital-intensive sectors documented at the industry level.

Public firms (Panel B) show small coefficients that vary in sign across periods, with no consistent pattern of persistent decline or recovery, consistent with their resilience to local disaster shocks.

4.4 Heterogeneity by Disaster Characteristics

In Online Appendix Table OA4, we examine heterogeneity across three additional dimensions, namely disaster type (named storms, coastal storms, wildfires, other storms, and floods), disaster duration, and disaster predictability. Results for named storms, coastal storms, wildfires, and other storms are broadly consistent with the main findings. Floods, after controlling for other disaster types, show small positive average effects, which we interpret as reflecting the smaller residual flood events remaining after major catastrophic flooding is absorbed by the named-storm and coastal-storm indicators. We do not detect a consistent pattern of attenuation by disaster duration or predictability.

4.5 Stock Market Reactions for Public Firms

Our primary analyses focus on operating performance, which is directly comparable across public and private firms. For public firms, we can also examine stock market reactions to assess how investors perceive climate risk exposure. Using industry-adjusted abnormal returns around disaster declarations (detailed methodology and results in Online Appendix Table OA5.1), we find modest average effects: market capitalization declines by approximately 1.3% in a three-day window. However, this effect is concentrated in specific industries (consumer durables, manufacturing, business equipment) and disaster types (named storms, floods), with most combinations showing no significant response. These findings complement our operating performance results: public firms appear resilient to climate disasters across both operational and market-based measures, reinforcing the contrast with private firm vulnerability.

5 Conclusions

Climate disclosure regulations are expanding globally. The SEC's 2024 rules, Europe's CSRD, and ISSB standards adopted in over 30 jurisdictions all require public firms to report material climate risks, premised on the assumption that these firms face significant exposure. As jurisdictions including Singapore, the UK, and Nigeria consider extending requirements to private firms, a fundamental question arises: where do climate costs actually fall? We test this by comparing how public and private firms respond to climate disasters.

Using FEMA disaster declarations matched to establishment-level data for 8.9 million private and 13,513 public U.S. firms, we document a striking divergence. Public firms show no significant operating performance effects on average, with sales growth at public firms' local operations in disaster-affected counties statistically indistinguishable from operations in unaffected counties. This null result holds at the aggregate level and for most industries, with small exceptions in healthcare and finance. This pattern is consistent with public firms' geographic diversification, as the median public firm operates across more than 400 counties in 46 states, providing a natural hedge against localized shocks.

Private firms experience significant effects, with sales declining 0.7% on average when disasters strike, with persistent declines in capital-intensive industries. We examine geographic diversification and access to credit as candidate mechanisms. Both partially explain the public-private differential. Single-state private firms experience 0.8% declines versus no significant impact for diversified firms, and counties with greater bank coverage show attenuated disaster effects. However, neither mechanism protects firms in all industries. Diversified manufacturing firms experience declines indistinguishable from concentrated firms, and local banking presence does not attenuate effects in manufacturing or healthcare. This pattern suggests that disaster vulnerability in some industries reflects features of production that firm-level adaptation cannot easily address.

Our analysis of government assistance through SBA loans is suggestive rather than causal, as SBA loan availability is endogenous to disaster severity and county characteristics. Local bank coverage, which is determined by long-run market conditions rather than disaster response, provides corroborating evidence. The consistency between the two analyses supports the interpretation that credit access contributes to the public-private differential, though we cannot fully rule out confounding factors.

Our findings have direct implications for the ongoing international debate about the scope of climate disclosure requirements. Large, diversified public companies, which are required to disclose, show no aggregate effects from climate disasters. Small, concentrated private businesses, which represent 99% of U.S. firms and are excluded from disclosure requirements, bear disproportionate costs. This creates a gap between where standardized climate risk information exists and where climate costs actually fall. We do not prescribe a particular policy response, as extending disclosure mandates to private firms may impose prohibitive compliance costs. However, our evidence provides empirical grounding for standard setters evaluating how to address climate risk across the economy. Our industry heterogeneity results further suggest that standard setters might consider industry-tailored approaches, as manufacturing, retail, chemicals, and healthcare emerge as the most disaster-vulnerable industries for private firms. More broadly, our findings also highlight an information gap. Investors in private firms, including banks, private equity funds, and disaster assistance programs, lack standardized climate risk information for the firms most vulnerable to climate shocks.

Our paper is subject to several limitations. We examine acute physical disasters, not chronic climate adaptation or transition risks. We cannot observe insurance coverage that might further explain variation in disaster impacts. Survivorship bias may also affect our estimates if the most severely affected operations exit the sample. As discussed in Section 4.1.2, exit rates are only modestly higher for disaster-affected operations (approximately one percentage point), which suggests that survivorship bias biases our estimates downward but is unlikely to fully explain our findings. We therefore interpret our estimates as lower bounds on true disaster effects. Despite these limitations, our findings establish that climate vulnerability falls disproportionately on private firms, suggesting that research and policy focused solely on public companies may understate aggregate climate costs and overlook the firms most affected.

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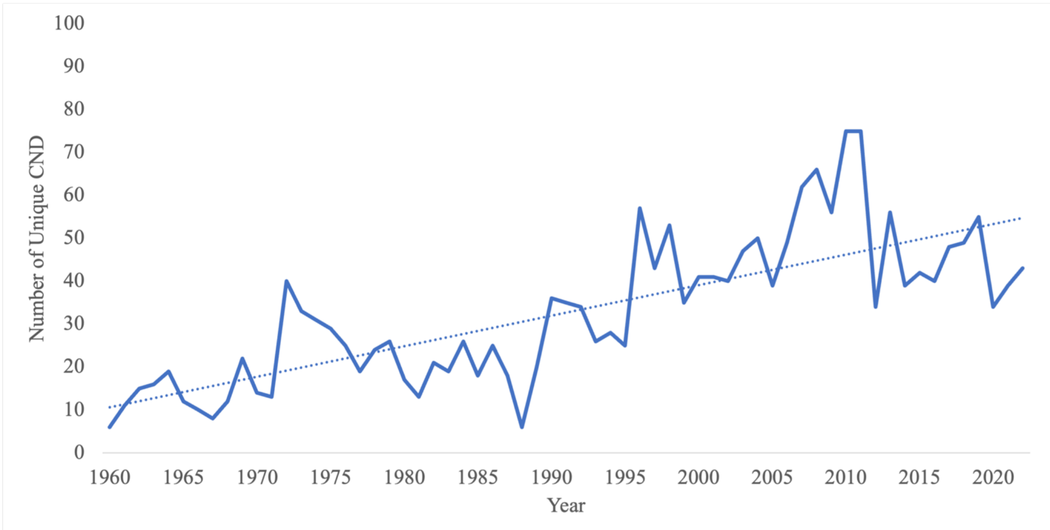
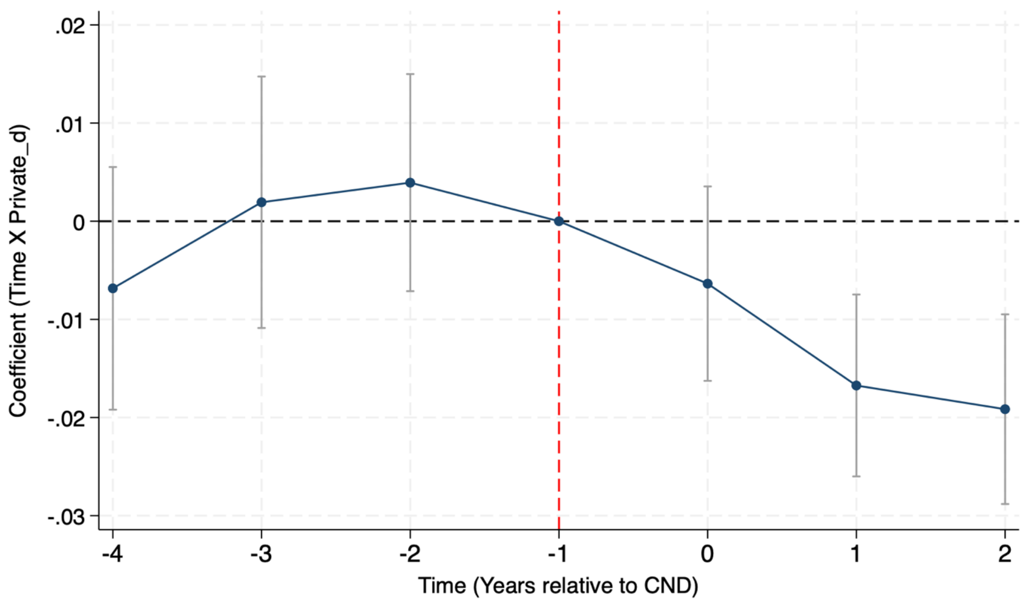
Figures

Figure 1: Unique CNDs Declared as Major Disasters by FEMA



This figure plots the number of unique CNDs declared as major disasters by FEMA used in our analyses. The dotted line represents the fitted trendline. Source: FEMA.

Figure 2: Parallel Trends



This figure plots the event-time coefficient from

$$Change\_Sales_{i,t,l,j} = \alpha + \sum_{k=-4,\, k\neq -1}^{2} \beta_k \, Private\_d_{i,t} \times Time_{t+k} + \sum_{k=-4,\, k\neq -1}^{2} \gamma_k \, Time_{t+k}$$
$$+ \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}.$$

The dependent variable is sales growth, with $Sales_{i,t,l,j}$ being the total sales volume of parent firm i in year t in county l across all its business units operating in industry j. $Private\_d$ is an indicator variable equal to one if firm is not a publicly listed firm, and zero otherwise. $Time_{l,t+k}$ is an indicator variable that takes the value one if county l is k years relative to its first CND experience, for $k \in \{-4, -3, -2, 0, 1, 2\}$, and zero otherwise. The coefficient at $k = -1$ is normalized to zero and serves as the base period. The plotted β_k coefficients test whether private and public firms followed parallel pre-trends prior to disaster exposure. The sample consists of first-time disaster exposure for each firm-county pair, requiring four clean pre-event years and two clean post-event years (no other disasters in the window). Confidence intervals are constructed at the 95% level. Standard errors are clustered at the parent firm level.

Tables

Table 1: Summary Descriptives

Panel A: Infogroup Public Firm Sample						
	N.	Mean	Median	Std. Dev.	P25	P75
Change_Sales	3,293,611	0.190	0.039	0.588	−0.221	0.460
Disaster_d	3,293,611	0.243	0	0.429	0	0
Sales ($ thousands)	3,293,611	23,655	2,891	200,038	795	10,602
Num of Employees	3,293,611	181.4	23	2,469.7	8	76
Num_County	178,399	730.9	469	766.2	129	1,134
Num_State	178,399	38.3	46	15.7	30	51
Exposed_Sales	178,399	0.041	0.001	0.178	0.000	0.005
Panel B: Infogroup Private Firm Sample						
	N.	Mean	Median	Std. Dev.	P25	P75
Change_Sales	26,884,761	0.125	0.007	0.554	−0.273	0.376
Disaster_d	26,884,761	0.257	0	0.437	0	1
Sales ($ thousands)	26,884,761	2,584	584	34,113	280	1,374
Num of Employees	26,884,761	11.4	4	92.8	2	7
Num_County	25,402,004	19.0	1	146.2	1	1
Num_State	25,402,004	2.4	1	7.2	1	1
Exposed_Sales	25,402,004	0.942	1	0.230	1	1

This table presents descriptive statistics for key variables used in our analyses. We use two units of analysis in this table. The first four variables in each panel are reported at the firm-county-industry-year level (the same as our regression sample), capturing each parent firm's local operations in a given county and industry. The remaining three variables (*Num_County*, *Num_State*, and *Exposed_Sales*) reflect firm-wide geographic exposure and are computed at the parent-firm-year level. Panels A and B present distributional statistics for the Infogroup sample for public and private firms, respectively. All variable definitions appear in Appendix A.

Table 2: Impact of CND on Private and Public Firms

	Public Firms		Private Firms		Diff. in Coefficient
	N	*Disaster_d*	N	*Disaster_d*	(4) − (2)
Industry	(1)	(2)	(3)	(4)	(5)
All	3,293,611	0.000	26,884,761	-0.007^{***}	-0.007^{***}
		(0.20)		(−22.22)	(−7.61)
Manufacturing	67,439	−0.007	584,526	-0.021^{***}	-0.014^{***}
		(−1.47)		(−12.67)	(−3.06)
Shops	1,686,343	−0.001	8,910,830	-0.010^{***}	-0.009^{***}
		(−0.54)		(−18.55)	(−6.72)
Chemicals	14,110	−0.018	26,331	-0.018^{**}	0.000
		(−1.59)		(−2.11)	(0.00)
Energy	22,435	−0.010	63,667	0.011^{*}	0.021^{*}
		(−0.97)		(1.73)	(1.73)
Business Equipment	46,474	−0.007	277,830	0.009^{***}	0.016^{***}
		(−0.99)		(3.19)	(2.12)
Telecom	94,457	0.000	170,737	0.021^{***}	0.021^{***}
		(0.06)		(4.80)	(3.04)
Utilities	24,588	0.002	62,661	0.008	0.006
		(0.17)		(1.60)	(0.56)
Healthcare	111,619	-0.013^{**}	3,777,379	-0.041^{***}	-0.028^{***}
		(−2.49)		(−65.08)	(−5.60)
Consumer Nondurables	55,756	-0.010^{*}	932,219	0.022^{***}	0.032^{***}
		(−1.79)		(14.06)	(5.41)
Consumer Durables	15,265	−0.009	129,447	−0.001	0.008
		(−0.55)		(−0.22)	(0.41)
Finance	465,170	0.008^{***}	2,564,260	0.012^{***}	0.004^{*}
		(3.43)		(12.01)	(1.73)
Other	681,449	0.000	8,938,765	0.006^{***}	0.006^{***}
		(0.23)		(10.65)	(3.09)
Parent Firm FE	Yes		Yes		
County FE	Yes		Yes		
Year FE	Yes		Yes		
Clustering	Parent Firm level		Parent Firm level		

The table presents regression summary statistics from estimating the following equation separately for each of the 12 Fama-French industries, for both private and public firms. The dependent variable is sales growth, with $Sales_{i,t,l,j}$ being the total sales volume of parent firm i in year t in county l across all its business units operating in industry j. $Disaster\_d_{l,t}$ is an indicator variable that takes the value one if county l experienced any CND in year t, and zero otherwise. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the parent firm level. T-statistics are reported in parentheses. All variable definitions appear in Appendix A.

Table 3: Impact of CND based on Geographical Diversification

Panel A: Impact of CND based on Geographic Diversification — Private Firms

	Concentrated Firms		Diversified Firms	
	N	*Disaster_d*	N	*Disaster_d*
Industry	(1)	(2)	(3)	(4)
All	25,363,099	-0.008^{***}	1,515,659	0.001
		(−23.44)		(0.94)
Consumer Nondurables	909,882	0.023^{***}	21,728	−0.005
		(14.37)		(−0.47)
Consumer Durables	121,817	−0.000	7,267	−0.002
		(−0.01)		(−0.11)
Manufacturing	553,204	-0.021^{***}	30,523	-0.022^{***}
		(−12.34)		(−2.76)
Energy	60,861	0.012^{*}	2,501	−0.020
		(1.91)		(−0.56)
Chemicals	22,374	-0.022^{**}	3,665	0.011
		(−2.42)		(0.47)
Business Equipment	266,659	0.010^{***}	10,464	−0.008
		(3.60)		(−0.48)
Telecom	159,075	0.022^{***}	11,188	0.002
		(4.85)		(0.19)
Utilities	61,226	0.008	1,231	0.029
		(1.41)		(0.69)
Shops	8,092,591	-0.011^{***}	816,084	−0.002
		(−19.08)		(−0.92)
Healthcare	3,727,204	-0.042^{***}	49,644	0.003
		(−66.70)		(0.41)
Finance	2,379,775	0.012^{***}	183,641	0.007^{*}
		(12.33)		(1.86)
Other	8,563,422	0.007^{***}	373,193	0.004
		(10.92)		(1.49)
Parent Firm FE	Yes		Yes	
County FE	Yes		Yes	
Year FE	Yes		Yes	
Clustering	Parent Firm level		Parent Firm level	

Table 3 (Continued): Impact of CND based on Geographical Diversification

Panel B: Impact of CND based on Geographic Diversification — Public Firms

	Concentrated Firms		Diversified Firms	
	N	*Disaster_d*	N	*Disaster_d*
Industry	(1)	(2)	(3)	(4)
All	126,662	−0.000	3,164,801	0.000
		(−0.05)		(0.26)
Consumer Nondurables	2,495	0.005	52,940	−0.010
		(0.14)		(−1.65)
Consumer Durables	1,465	−0.106**	13,555	0.003
		(−2.54)		(0.22)
Manufacturing	4,109	0.007	62,919	−0.007
		(0.30)		(−1.42)
Energy	1,570	−0.077	20,671	−0.009
		(−1.60)		(−0.82)
Chemicals	579	0.029	13,405	−0.019
		(0.41)		(−1.63)
Business Equipment	5,360	0.033	40,658	−0.010
		(1.46)		(−1.35)
Telecom	2,933	−0.043	91,327	0.002
		(−1.06)		(0.37)
Utilities	1,490	0.015	22,893	0.001
		(0.33)		(0.12)
Shops	28,783	−0.016	1,656,624	−0.000
		(−1.46)		(−0.32)
Healthcare	10,051	−0.044***	101,307	−0.012**
		(−2.94)		(−2.21)
Finance	29,241	0.015	435,219	0.008***
		(1.50)		(3.33)
Other	30,416	0.011	650,072	0.000
		(1.05)		(0.05)
Parent Firm FE	Yes		Yes	
County FE	Yes		Yes	
Year FE	Yes		Yes	
Clustering	Parent Firm level		Parent Firm level	

The following tables present regression summary statistics from estimating the following equation separately for Geographically Concentrated and Diversified firms. The dependent variable is sales growth, with $Sales_{i,t,l,j}$ being the total sales volume of parent firm i in year t in county l across all its business units operating in industry j. $Disaster\_d_{l,t}$ is an indicator variable that takes the value one if county l experienced any CND in year t, and zero otherwise. A firm is *Concentrated* if it has business units only in one state and *Diversified* if its business units are present in more than 1 state. Panel A presents the results for private firms. Panel B presents the results for public firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the parent firm level. T-statistics are reported in parentheses. All variable definitions appear in Appendix A.

Table 4: Role of Credit Access for Private Firms

Panel A: Role of Government Financial Assistance and Private Firms

Industry	N	*SBA_d* × *Disaster_d*	*Disaster_d*	*SBA_d*
	(1)	(2)	(3)	(4)
All Industries	18,682,796	0.027^{***}	-0.017^{***}	-0.004^{***}
		(29.01)	(−35.73)	(−5.61)
Consumer Nondurables	646,680	0.033^{***}	0.019^{***}	0.035^{***}
		(6.58)	(7.83)	(10.47)
Consumer Durables	83,039	0.075^{***}	-0.014^{**}	-0.078^{***}
		(5.98)	(−2.12)	(−9.63)
Manufacturing	367,577	0.028^{***}	-0.029^{***}	-0.052^{***}
		(5.11)	(−10.82)	(−14.19)
Energy	40,526	0.078^{***}	-0.026^{***}	-0.049^{***}
		(4.06)	(−2.72)	(−3.61)
Chemicals	18,155	0.019	−0.016	-0.033^{*}
		(0.78)	(−1.23)	(−1.89)
Business Equipment	213,025	0.028^{***}	-0.008^{**}	0.022^{***}
		(3.60)	(−2.12)	(4.21)
Telecom	112,081	0.111^{***}	0.012^{*}	-0.122^{***}
		(7.97)	(1.82)	(−13.02)
Utilities	42,387	0.019	0.017^{**}	-0.024^{*}
		(1.01)	(2.29)	(−1.81)
Shops	6,000,291	0.031^{***}	-0.026^{***}	0.003^{***}
		(19.21)	(−30.44)	(3.17)
Healthcare	2,688,470	0.027^{***}	-0.066^{***}	-0.008^{***}
		(15.37)	(−68.57)	(−7.55)
Finance	1,938,385	-0.013^{***}	0.016^{***}	0.027^{***}
		(−5.20)	(12.03)	(14.79)
Others	6,215,426	0.039^{***}	-0.002^{*}	-0.010^{***}
		(21.98)	(−1.89)	(−8.37)
Parent Firm FE	Yes			
County FE	Yes			
Year FE	Yes			
Clustering	Parent Firm level			

Table 4 (Continued): Role of Credit Access for Private Firms

Panel B: Role of Lending Bank Relationship and Private Firms

Industry	N	*Above_Median_Bank* × *Disaster_d*	*Disaster_d*	*Above_Median_ Bank*
	(1)	(2)	(3)	(4)
All Industries	26,494,506	0.022^{***}	-0.028^{***}	0.019^{***}
		(16.00)	(−20.94)	(10.81)
Consumer Nondurables	578,291	−0.005	-0.017^{**}	0.054^{***}
		(−0.68)	(−2.22)	(5.56)
Consumer Durables	8,774,790	0.017^{***}	-0.026^{***}	0.013^{***}
		(7.51)	(−11.76)	(4.60)
Manufacturing	26,010	−0.002	−0.020	0.005
		(−0.07)	(−0.64)	(0.12)
Energy	63,160	-0.033^{**}	0.038^{***}	-0.038^{*}
		(−2.15)	(2.72)	(−1.70)
Chemicals	274,150	0.048^{**}	-0.036^{*}	0.069^{***}
		(2.45)	(−1.90)	(3.43)
Business Equipment	167,057	0.041^{***}	−0.018	−0.009
		(2.78)	(−1.31)	(−0.40)
Telecom	62,234	0.013	−0.003	0.019
		(1.06)	(−0.23)	(1.23)
Utilities	3,721,941	0.022^{***}	-0.062^{***}	0.028^{***}
		(5.71)	(−16.23)	(5.62)
Shops	924,053	0.037^{***}	-0.011^{*}	−0.009
		(6.15)	(−1.96)	(−1.11)
Healthcare	127,704	0.013	−0.015	−0.023
		(0.70)	(−0.81)	(−0.92)
Finance	2,522,931	0.017^{***}	−0.005	0.005
		(4.23)	(−1.38)	(0.90)
Others	8,813,198	0.031^{***}	-0.024^{***}	0.027^{***}
		(12.29)	(−9.89)	(8.12)
Parent Firm FE	Yes			
County FE	Yes			
Year FE	Yes			
Clustering	Parent Firm level			

Panel A presents regression summary statistics from estimating the following equation separately for each of the 12 Fama-French industries for private firms. Panel B presents the corresponding bank-relationship specification. The dependent variable is sales growth, with $Sales_{i,t,l,j}$ being the total sales volume of parent firm i in year t in county l across all its business units operating in industry j. $Disaster\_d_{l,t}$ is an indicator variable that takes the value one if county l experienced any CND in year t, and zero otherwise. $SBA\_d_{l,t}$ is an indicator variable that takes value one if county l has received any SBA disaster financial assistance in year t, and zero otherwise. *Above_Median_Bank* is an indicator equal to one if the number of banks in county l meets or exceeds the year-specific median, and zero otherwise. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the parent firm level. T-statistics are reported in parentheses. All variable definitions appear in Appendix A.

Table 5: Persistence of Effects

Panel A: Dynamic Impact of all CND on Private Firms

Industry	N (1)	$k=2$ *Disaster_d* (2)	$k=3$ *Disaster_d* (3)	$k=4$ *Disaster_d* (4)	$k=5$ *Disaster_d* (5)
All	14,794,977	0.003^{***}	0.002^{***}	0.001^{***}	0.002^{***}
		(41.38)	(30.34)	(10.26)	(34.77)
Manufacturing	335,861	-0.005^{***}	-0.009^{***}	-0.004^{***}	-0.011^{***}
		(−11.46)	(−19.06)	(−2.87)	(−27.38)
Shops	5,016,740	0.004^{***}	0.001^{***}	0.002^{***}	0.003^{***}
		(28.81)	(5.86)	(3.42)	(25.19)
Chemicals	11,723	−0.003	0.001	0.004	-0.013^{***}
		(−1.43)	(0.22)	(0.48)	(−6.14)
Energy	30,320	0.001	-0.005^{***}	0.003	0.001
		(0.34)	(−3.47)	(0.54)	(0.51)
Business Equipment	128,458	0.001	0.000	-0.006^{**}	0.002^{**}
		(1.37)	(0.03)	(−2.22)	(2.00)
Telecom	70,636	−0.001	-0.007^{***}	-0.006^{*}	-0.002^{**}
		(−0.72)	(−5.46)	(−1.77)	(−2.18)
Utilities	36,119	0.001	0.002^{*}	-0.012^{**}	-0.002^{*}
		(0.85)	(1.86)	(−2.14)	(−1.83)
Healthcare	2,290,097	0.001^{***}	-0.005^{***}	0.002^{***}	0.002^{***}
		(10.16)	(−38.66)	(3.63)	(20.77)
Consumer Nondurables	509,030	0.007^{***}	0.004^{***}	0.000	0.006^{***}
		(16.64)	(11.57)	(0.06)	(18.43)
Consumer Durables	58,683	-0.007^{***}	-0.010^{***}	-0.005^{***}	-0.012^{***}
		(−7.71)	(−10.68)	(−3.33)	(−15.11)
Finance	1,377,029	0.003^{***}	0.000	−0.001	0.003^{***}
		(11.91)	(0.09)	(−1.48)	(12.56)
Other	4,834,901	0.004^{***}	-0.001^{***}	-0.001^{***}	0.003^{***}
		(25.52)	(−10.37)	(−11.63)	(25.99)
Parent Firm FE		Yes	Yes	Yes	Yes
County FE		Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes
Clustering			Parent Firm level		

Table 5 (Continued): Persistence of Effects

Panel B: Dynamic Impact of all CND on Public Firms

Industry	N (1)	$k = 2$ *Disaster_d* (2)	$k = 3$ *Disaster_d* (3)	$k = 4$ *Disaster_d* (4)	$k = 5$ *Disaster_d* (5)
All	1,622,671	0.003^{***}	-0.002^{**}	0.006^{***}	0.001^{*}
		(3.85)	(−2.30)	(3.27)	(1.74)
Manufacturing	18,227	−0.005	−0.004	0.017	−0.004
		(−1.50)	(−1.22)	(0.89)	(−0.91)
Shops	938,564	0.002^{**}	−0.001	0.005^{**}	0.000
		(2.02)	(−0.88)	(2.09)	(0.43)
Chemicals	2,524	−0.011	0.002	−0.071	0.006
		(−1.36)	(0.22)	(−1.65)	(0.81)
Energy	6,847	−0.003	−0.009	0.032	0.006
		(−0.36)	(−1.19)	(0.85)	(0.74)
Business Equipment	10,147	0.007	0.000	0.024	−0.003
		(1.42)	(0.05)	(0.66)	(−0.62)
Telecom	36,860	-0.009^{**}	0.003	−0.010	−0.006
		(−1.99)	(0.50)	(−1.12)	(−1.23)
Utilities	5,431	0.001	−0.006	0.108^{*}	0.008
		(0.06)	(−0.61)	(1.76)	(1.03)
Healthcare	40,004	0.002	-0.007^{**}	-0.018^{**}	−0.001
		(0.56)	(−2.45)	(−2.09)	(−0.26)
Consumer Nondurables	15,331	−0.001	0.003	0.030	−0.003
		(−0.16)	(0.46)	(1.31)	(−0.85)
Consumer Durables	2,168	−0.008	0.011	−0.011	−0.006
		(−0.93)	(1.30)	(−0.10)	(−0.82)
Finance	225,020	0.002	-0.004^{*}	0.002	0.004^{**}
		(0.80)	(−1.89)	(0.41)	(2.12)
Other	317,485	0.008^{***}	−0.001	0.014^{***}	0.003^{**}
		(4.97)	(−1.05)	(4.02)	(2.11)
Parent Firm FE		Yes	Yes	Yes	Yes
County FE		Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes
Clustering		Parent Firm level			

The following table presents regression summary statistics from estimating the following equation. The dependent variable is sales growth in the k-th year post-CND, for $k = 2, 3, 4, 5$. $Disaster\_d_{l,t}$ is an indicator variable that takes the value one if county l experienced any CND in year t, and zero otherwise. Panel A presents the results for private firms and Panel B presents the results for public firms. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the parent firm level. T-statistics are reported in parentheses. All variable definitions appear in Appendix A.

Appendix A Variable Definitions

Table A1: Variable Definitions

Panel A: Disaster Variables		
Variable	Description	Data Source
Disaster_d	Indicator equal to one if county l experienced any CND in year t, and zero otherwise.	FEMA

Panel B: Infogroup Variables		
Variable	Description	Data Source
Change_Sales	Year-over-year percentage change in $Sales_{i,t,l,j}$, computed as $\frac{Sales_{i,t,l,j} - Sales_{i,t-1,l,j}}{Sales_{i,t-1,l,j}}$.	Infogroup
Sales	Total sales volume (in \$ thousands) of parent firm i in year t in county l across all its business units operating in industry j.	Infogroup
Private_d	Indicator equal to 1 if firm is not a publicly listed firm, and zero otherwise.	Infogroup, Compustat
Num of Employees	Total number of employees of parent firm i in year t in county l across all its business units operating in industry j.	Infogroup
Num_County	Number of counties a firm has its subsidiaries located.	Infogroup
Num_State	Number of states a firm has its subsidiaries located.	Infogroup
Exposed_Sales	Share of firm's total sales located in counties that experienced a CND in year t.	Infogroup

Panel C: SBA Variables		
Variable	Description	Data Source
SBA	Amount of disaster financial assistance loan issued by SBA to a county in time period t.	SBA
SBA_d	Indicator equal to one if SBA issued any disaster financial assistance loan to any firm in county l during time period t.	SBA
Above_Median_Bank	Indicator equal to one if the number of banks in a county equals or exceeds the year-specific median.	FDIC Summary of Deposits

Appendix B Sales Computation

Let's say that in the year 2000, there was a Parent Firm A with six subsidies located across three counties and operating in two different industries. The following tables illustrate the sales from each of the business units.

Then, sales for Company A in Kings County from its Consumer Durable business will be 250 (100 from A1 +150 from A2). Similarly, $Sales_{A,2000,\text{New York County},\text{Consumer Durables}}$ will be 160 (60 from A4 +100 from A5), and $Sales_{A,2000,\text{New York County},\text{Consumer Non Durables}}$ will be 70 (from A6).

Year	Parent Company	Subsidiary	County	Industry	Sales
2000	A	A1	Kings County	Consumer Durables	100
2000	A	A2	Kings County	Consumer Durables	150
2000	A	A3	Queens County	Consumer Durables	200
2000	A	A4	New York County	Consumer Durables	60
2000	A	A5	New York County	Consumer Durables	100
2000	A	A6	New York County	Consumer Non Durables	70
				Total Sales	680

Online Appendix

Who Bears Climate Risk? Differential Impacts on Public and Private Firms

Contents

OA1. Variable Definitions

Table OA1: Variable Definitions

Panel A: Disaster Variables		
Variable	Description	Data Source
Disaster_d	Indicator equal to one if county l experienced any CND in year t, and zero otherwise.	FEMA
Named Disasters	Indicator equal to one if firm experienced any named disaster (for e.g. Hurricane Katrina) at any of its establishment location in period t.	FEMA
Coastal Storms	Indicator equal to one if firm experienced any coastal storm (other than named disaster) at any of its establishment location in period t.	FEMA
Fires	Indicator equal to one if firm experienced any fires at any of its establishment location in period t.	FEMA
Other Storms	Indicator equal to one if firm experienced any other storm (like snowstorms) at any of its establishment location in period t.	FEMA
Floods	Indicator equal to one if firm experienced flooding at any of its establishment location in period t.	FEMA
Longer Disasters	Indicator equal to one if firm experienced any disaster lasting longer than 30 days at any of its location in period t.	FEMA
Shorter Disasters	Indicator equal to one if firm experienced any disaster lasting 30 days or less at any of its location in period t.	FEMA
Predictable Disasters	Indicator equal to one if the state experienced similar disaster in the same month in year $t-1$.	FEMA
Unpredictable Disasters	Indicator equal to one if the disaster is not a Predictable Disaster.	FEMA
Panel B: Infogroup Variables		
Variable	Description	Data Source
Change_Sales	Year-over-year percentage change in $Sales_{i,t,l,j}$, computed as $\frac{Sales_{i,t,l,j} - Sales_{i,t-1,l,j}}{Sales_{i,t-1,l,j}}$.	Infogroup
Sales	Total sales volume (in \$ thousands) of parent firm i in year t in county l across all its business units operating in industry j.	Infogroup
Private_d	Indicator equal to 1 if firm is not a publicly listed firm, and zero otherwise.	Infogroup, Compustat

Table OA1 (Continued): Variable Definitions

Panel B: Infogroup Variables (continued)		
Variable	Description	Data Source
Num of Employees	Total number of employees of parent firm i in year t in county l across all its business units operating in industry j.	Infogroup
Num_County	Number of counties a firm has its subsidiaries located.	Infogroup
Num_State	Number of states a firm has its subsidiaries located.	Infogroup
Exposed_Sales	Share of firm's total sales located in counties that experienced a CND in year t.	Infogroup

Panel C: SBA Variables		
Variable	Description	Data Source
SBA	Amount of disaster financial assistance loan issued by SBA to a county in time period t.	SBA
SBA_d	Indicator equal to one if SBA issued any disaster financial assistance loan to any firm in county l during time period t.	SBA
Above_Median_Bank	Indicator equal to one if the number of banks in a county equals or exceeds the year-specific median.	FDIC Summary of Deposits

Panel D: Return Variables		
Variable	Description	Data Source
Event[$-1,+1$]	Indicator equal to one if day t is in the event window (i.e., the three-day period from $t-1$ to $t+1$ where t is the first trading date post CND) and any of the firm i's subsidiary is in a county affected by a CND, and zero otherwise.	Infogroup
Event[$-5,+5$]	Indicator equal to one if day t is in the event window (i.e., the eleven-day period from $t-5$ to $t+5$ where t is the first trading date post CND) and any of the firm i's subsidiary is in a county affected by a CND, and zero otherwise.	Infogroup
Event_pre20	Indicator variable equal to 1 if day t is in 20 days before the event window, and any of the firm i's subsidiary is in a county affected by a CND, and zero otherwise.	Infogroup
Event_post20	Indicator variable equal to 1 if day t is in 20 days after the event window, and any of the firm i's subsidiary is in a county affected by a CND, and zero otherwise.	Infogroup
Abnormal Return	Daily return for firm i on day t minus the equally weighted return of all the firms in the same 12-digit Fama French industry as firm i.	CRSP

Panel E: Control variables for Event Study		
Variable	Description	Data Source
Lev	Total Debt ("DTQ") / Total Assets ("ATQ").	Compustat
MB	Market value of common equity / Book value of common equity.	Compustat
ROA	Earnings before Interest and Tax ("EBITQ") / Total Assets ("ATQ").	Compustat
Ln(ME)	Natural log of Market capital ("PRC" $\times$ "SHROUT" / 1000).	CRSP

OA2. Impact of CND on Private Firms Using PSM Matched Sample

Table OA2: Impact of CND on Private Firms Using PSM Matched Sample

	Public Firms		Private Firms	
	N	*Disaster_d*	N	*Disaster_d*
Industry	(1)	(2)	(3)	(4)
All	1,228,173	0.001	23,816,005	-0.008^{***}
		(0.21)		(-35.15)
Manufacturing	32,288	-0.007	528,957	-0.012^{***}
		(-0.73)		(-9.44)
Shops	587,714	0.004	7,747,252	-0.005^{***}
		(0.79)		(-12.42)
Chemicals	5,074	-0.036^{*}	21,082	-0.017^{**}
		(-1.83)		(-2.53)
Energy	8,431	0.019	54,558	0.004
		(0.95)		(0.88)
Business Equipment	19,514	0.004	249,466	0.014^{***}
		(0.28)		(6.90)
Telecom	21,273	0.033^{*}	147,323	0.019^{***}
		(1.65)		(6.33)
Utilities	5,267	-0.029	54,345	0.004
		(-0.92)		(1.10)
Healthcare	54,877	-0.028^{***}	3,582,581	-0.041^{***}
		(-2.60)		(-81.85)
Consumer Nondurables	24,032	0.052^{**}	835,065	0.013^{***}
		(2.19)		(10.75)
Consumer Durables	4,197	-0.033	115,052	-0.004
		(-1.41)		(-1.36)
Finance	141,356	-0.000	2,292,027	0.005^{***}
		(-0.03)		(6.63)
Other	314,501	-0.007	7,776,769	-0.001^{*}
		(-1.05)		(-1.79)
Parent Firm FE	Yes		Yes	
County FE	Yes		Yes	
Year FE	Yes		Yes	
Clustering	Parent Firm level		Parent Firm level	

The table presents regression summary statistics from estimating the following equation separately for each of the 12 Fama-French industries for private firms. The dependent variable is sales growth, with $Sales_{i,t,l,j}$ being the total sales volume of parent firm i in year t in county l across all its business units operating in industry j. $Disaster\_d_{l,t}$ is an indicator variable that takes the value one if county l experienced any CND in year t, and zero otherwise. Public firm sample consist of the nearest three neighbors based on the natural log of sales volume and the natural log of number of employees in the year prior to the CND. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the parent firm level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

OA3. Role of Credit Access for Public Firms

Table OA3: Role of Credit Access for Public Firms

Panel A: Role of Government Financial Assistance and Public Firms

Industry	N (1)	$SBA\_d \times Disaster\_d$ (2)	$Disaster\_d$ (3)	SBA_d (4)
All Industries	2,667,523	0.004*	−0.001	0.002
		(1.87)	(−0.60)	(1.24)
Consumer Nondurables	46,373	−0.002	−0.004	−0.025
		(−0.11)	(−0.40)	(−1.27)
Consumer Durables	12,936	−0.004	−0.004	0.012
		(−0.14)	(−0.22)	(0.56)
Manufacturing	55,329	0.011	−0.008	−0.014*
		(0.89)	(−1.23)	(−1.76)
Energy	18,512	−0.004	−0.017	0.019
		(−0.16)	(−1.25)	(1.18)
Chemicals	11,935	−0.006	−0.011	−0.002
		(−0.20)	(−0.84)	(−0.11)
Business Equipment	39,265	0.017	−0.008	−0.022**
		(0.98)	(−0.91)	(−2.19)
Telecom	76,196	−0.005	0.005	−0.009
		(−0.36)	(0.65)	(−1.02)
Utilities	20,750	0.012	0.008	−0.012
		(0.44)	(0.69)	(−0.83)
Shops	1,350,721	0.001	−0.002	0.005**
		(0.43)	(−1.24)	(2.58)
Healthcare	95,512	0.016	−0.018**	−0.011
		(1.42)	(−2.51)	(−1.46)
Finance	381,842	0.009*	0.008***	−0.003
		(1.81)	(2.67)	(−0.89)
Others	550,676	0.009*	−0.002	0.003
		(1.94)	(−0.92)	(0.81)
Parent Firm FE	Yes			
County FE	Yes			
Year FE	Yes			
Clustering	Parent Firm level			

Table OA3 (Continued): Role of Credit Access for Public Firms

Panel B: Role of Lending Bank Relationship and Public Firms

Industry	N	*Above_Median_Bank* × *Disaster_d*	*Disaster_d*	*Above_Median_ Bank*
	(1)	(2)	(3)	(4)
All Industries	3,270,586	-0.008^{**}	0.008^{*}	0.002
		(−1.97)	(1.93)	(0.54)
Consumer Nondurables	67,000	−0.015	0.007	0.016
		(−1.10)	(0.52)	(0.86)
Consumer Durables	1,674,870	-0.010^{*}	0.008	0.002
		(−1.80)	(1.55)	(0.53)
Manufacturing	14,056	0.009	−0.029	0.035
		(0.30)	(−1.11)	(0.73)
Energy	22,400	−0.017	0.004	0.044
		(−0.87)	(0.22)	(1.15)
Chemicals	45,979	0.012	−0.019	0.043
		(0.46)	(−0.68)	(1.11)
Business Equipment	93,734	0.000	0.000	−0.007
		(0.02)	(0.01)	(−0.43)
Telecom	24,497	−0.006	0.008	−0.026
		(−0.24)	(0.42)	(−1.17)
Utilities	110,639	0.014	-0.025^{**}	0.010
		(1.57)	(−2.57)	(0.74)
Shops	55,392	−0.007	−0.005	0.018
		(−0.56)	(−0.49)	(1.12)
Healthcare	15,201	-0.072^{***}	0.056^{***}	0.060^{**}
		(−5.62)	(5.02)	(2.08)
Finance	462,123	−0.013	0.019^{*}	−0.007
		(−1.15)	(1.78)	(−0.96)
Others	676,277	−0.006	0.006	−0.000
		(−0.58)	(0.63)	(−0.03)
Parent Firm FE	Yes			
County FE	Yes			
Year FE	Yes			
Clustering	Parent Firm level			

Panel A presents regression summary statistics from estimating the SBA specification separately for each of the 12 Fama-French industries for public firms. Panel B presents the corresponding bank-relationship specification. The dependent variable is sales growth. *Disaster_d*$_{l,t}$ is an indicator variable that takes the value one if county l experienced any CND in year t, and zero otherwise. *SBA_d*$_{l,t}$ is an indicator variable that takes value one if county l has received any SBA disaster financial assistance in year t, and zero otherwise. *Above_Median_Bank* is an indicator equal to one if the number of banks in county l meets or exceeds the year-specific median, and zero otherwise. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the parent firm level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

OA4. Heterogeneity by Disaster Characteristics

OA4.1 Disaster Type

We first examine variation by disaster type, categorizing disasters into five groups: named disasters, coastal storms, fires, other storms, and floods.[18] These types vary in severity and predictability. Named disasters such as hurricanes, though severe, are often predictable days in advance. In contrast, flash floods and fires may strike with little warning.

We estimate the following equation for public and private firms within each of the Fama-French 12 industries:

$$\begin{aligned} Change\_Sales_{i,t,l,j} = \alpha &+ \beta_1\, Named\, Disaster_{l,t} + \beta_2\, Coastal\, Storm_{l,t} + \beta_3\, Fire_{l,t} \\ &+ \beta_4\, Flood_{l,t} + \beta_5\, Other\, Storms_{l,t} + \text{Parent Firm FE} + \text{Year FE} \\ &+ \text{County FE} + \varepsilon_{i,t}. \end{aligned} \tag{5}$$

$Named\, Disaster_{l,t}$ is an indicator variable that takes the value of one if county l experienced any named disaster in year t, and zero otherwise. Similarly, $Coastal\, Storm_{l,t}$, $Fire_{l,t}$, $Flood_{l,t}$, and $Other\, Storms_{l,t}$ are also indicator variables that takes the value of one if county l experienced the respective type of CND in year t, and zero otherwise. This specification enables us to isolate the effect of each specific type of CND on local sales volumes, while holding constant exposure to other disaster types. Parent firm fixed effects absorb time-invariant firm characteristics, both observed and unobserved, that may correlate with both disaster exposure and operating performance. County fixed effects absorb time-invariant differences across counties, including baseline political environment and disaster preparedness. Year fixed effects absorb common annual shocks. We cluster standard errors at the parent firm level to account for within-firm correlation across the firm's multiple local operations (firm-county-industry cells) and over time.

Panel A of Table OA4 presents results for private firms. The results for all disaster types except floods are similar to the main findings. All types of storms (named, coastal, and others) and wildfires have a negative impact on private firm sales growth on average. One surprising result

[18] Named disasters are tropical storms which are given unique names by FEMA, such as Hurricane Katrina, Ian, and others.

is that, after controlling for all other disaster types, floods appear to have a positive association with private firm sales in most industries, with healthcare showing a negative flood coefficient and finance showing a coefficient indistinguishable from zero. One potential explanation is that named disasters, coastal storms, wildfires, and other storms already capture the major catastrophic events. The remaining floods are smaller, more frequent river or flash floods that do not cause significant business damage but may boost demand for repairs and replacements.

Panel B of Table OA4 presents results for public firms, which show more limited effects. Named disasters are negatively associated with sales growth in the shops, chemicals, energy, and healthcare sectors. This is consistent with named disasters being the most severe event type, including major hurricanes and tornadoes. Other storms also show negative associations in some industries (chemicals, healthcare, and others). The remaining disaster types show no significant effects on public firm sales, consistent with public firms' ability to absorb localized shocks through diversification.

Table OA4: Impact of CND – Based on CND Characteristics

Panel A: Impact of different CND on Private Firms

Industry	N (1)	*Named Disaster* (2)	*Coastal Storm* (3)	*Wildfire* (4)	*Other Storm* (5)	*Flood* (6)
All	24,380,197	-0.010^{***}	-0.084^{***}	-0.049^{***}	-0.014^{***}	0.003^{***}
		(−20.57)	(−8.71)	(−64.64)	(−45.69)	(6.05)
Manufacturing	549,858	-0.036^{***}	-0.185^{**}	-0.012^{***}	-0.020^{***}	0.043^{***}
		(−12.47)	(−2.48)	(−3.17)	(−11.56)	(18.55)
Shops	8,060,130	-0.021^{***}	0.006	-0.022^{***}	-0.015^{***}	0.006^{***}
		(−26.34)	(0.33)	(−17.68)	(−27.37)	(7.55)
Chemicals	24,299	−0.012	-0.117^{*}	-0.074^{***}	-0.024^{***}	0.059^{***}
		(−1.12)	(−1.87)	(−3.92)	(−2.80)	(4.72)
Energy	58,083	−0.008	−0.064	-0.061^{***}	−0.004	0.052^{***}
		(−1.15)	(−0.78)	(−3.35)	(−0.58)	(5.40)
Business Equipment	253,792	0.003	-0.093^{*}	0.005	−0.004	0.053^{***}
		(0.66)	(−1.67)	(0.81)	(−1.25)	(14.43)
Telecom	150,282	0.062^{***}	0.093	0.069^{***}	−0.002	0.031^{***}
		(10.31)	(1.26)	(7.12)	(−0.49)	(5.35)
Utilities	58,737	−0.007	0.106	0.067^{***}	−0.007	0.021^{***}
		(−0.87)	(0.34)	(4.57)	(−1.50)	(3.25)
Healthcare	3,625,821	-0.025^{***}	-0.243^{***}	-0.125^{***}	-0.023^{***}	-0.054^{***}
		(−25.78)	(−11.02)	(−77.59)	(−32.54)	(−60.57)
Consumer Nondurables	862,313	0.032^{***}	-0.147^{***}	-0.064^{***}	0.007^{***}	0.019^{***}
		(12.71)	(−2.94)	(−15.90)	(4.55)	(8.70)
Consumer Durables	120,455	-0.042^{***}	−0.100	0.064^{***}	-0.030^{***}	0.063^{***}
		(−6.41)	(−1.49)	(6.73)	(−7.13)	(11.75)
Finance	2,316,561	0.036^{***}	-0.060^{*}	-0.014^{***}	-0.005^{***}	−0.001
		(24.65)	(−1.73)	(−5.55)	(−4.91)	(−0.77)
Other	7,875,185	0.014^{***}	-0.123^{***}	-0.057^{***}	-0.013^{***}	0.023^{***}
		(15.55)	(−7.30)	(−40.79)	(−23.66)	(26.41)
Parent Firm FE, County FE, Year FE	Yes					
Clustering	Parent Firm level					

Panel A presents regression summary statistics for private firms estimating $Change\_Sales_{i,t,l,j} = \alpha + \beta_1\, Named\, Disaster_{l,t} + \beta_2\, Coastal\, Storm_{l,t} + \beta_3\, Fire_{l,t} + \beta_4\, Flood_{l,t} + \beta_5\, Other\, Storms_{l,t}$ + Parent Firm FE + Year FE + County FE + $\varepsilon_{i,t}$. *Named* $Disaster_{l,t}$ is an indicator equal to one if county l experienced any named disaster in year t, and zero otherwise. *Coastal* $Storm_{l,t}$, $Fire_{l,t}$, $Flood_{l,t}$, and *Other* $Storms_{l,t}$ are also indicators for the respective type of CND. *, **, *** denote significance at the 10%, 5%, 1% levels. T-statistics in parentheses; standard errors clustered at the parent firm level. All variable definitions in Online Appendix OA1.

Table OA4 (Continued): Impact of CND – Based on CND Characteristics

Panel B: Impact of different CND on Public Firms

Industry	N (1)	*Named Disaster* (2)	*Coastal Storm* (3)	*Wildfire* (4)	*Other Storm* (5)	*Flood* (6)
All	2,960,229	−0.001	−0.007	0.003	−0.001	0.002
		(−0.81)	(−0.36)	(1.15)	(−1.32)	(1.43)
Manufacturing	61,190	−0.003	−0.041	−0.002	0.002	0.012
		(−0.34)	(−0.20)	(−0.10)	(0.33)	(1.62)
Shops	1,526,834	-0.003^{**}	0.011	0.007^{**}	−0.000	−0.002
		(−1.96)	(0.38)	(2.10)	(−0.29)	(−1.16)
Chemicals	12,231	-0.038^{**}	—	−0.023	-0.026^{***}	0.032^{*}
		(−2.54)	—	(−0.79)	(−2.61)	(1.80)
Energy	19,715	-0.026^{**}	−0.052	0.024	−0.001	−0.012
		(−2.10)	(−0.43)	(1.01)	(−0.08)	(−0.77)
Business Equipment	40,978	−0.011	−0.086	−0.003	0.009^{*}	0.050^{***}
		(−1.10)	(−0.86)	(−0.21)	(1.65)	(4.78)
Telecom	82,701	0.000	0.064	0.017	0.005	−0.008
		(0.04)	(0.62)	(1.25)	(1.32)	(−0.89)
Utilities	21,375	−0.011	−0.082	−0.003	0.005	0.020
		(−0.70)	(−0.99)	(−0.11)	(0.53)	(1.01)
Healthcare	100,485	-0.014^{**}	−0.066	−0.015	-0.008^{*}	−0.003
		(−2.00)	(−0.76)	(−1.33)	(−1.84)	(−0.41)
Consumer Nondurables	49,583	0.007	0.013	−0.027	−0.005	0.013
		(0.81)	(0.05)	(−1.58)	(−0.96)	(1.21)
Consumer Durables	13,059	0.009	0.486	−0.033	−0.006	0.029
		(0.27)	(1.51)	(−1.27)	(−0.43)	(1.37)
Finance	416,766	0.006^{*}	−0.005	0.009^{*}	0.002	0.015^{***}
		(1.78)	(−0.10)	(1.83)	(1.08)	(4.14)
Other	606,275	0.001	−0.044	0.001	-0.006^{***}	−0.001
		(0.48)	(−0.82)	(0.16)	(−4.12)	(−0.25)
Parent Firm FE, County FE, Year FE	Yes					
Clustering	Parent Firm level					

Panel B presents the same specification as Panel A but estimated for public firms. "—" indicates the specification could not be estimated due to lack of variation. *, **, *** denote significance at the 10%, 5%, 1% levels. T-statistics in parentheses; standard errors clustered at the parent firm level. All variable definitions in Online Appendix OA1.

OA4.2 Disaster Duration

Next, we examine whether disaster duration affects sales impacts. Disasters that persist for longer periods may cause greater harm by prolonging business interruptions, delaying supply chain recovery, and depleting firms' financial resources. Conversely, short-duration events may allow firms to resume operations quickly. To test this, we estimate:

$$\begin{aligned} Change\_Sales_{i,t,l,j} = \alpha &+ \beta_1\, Longer\ Disaster_{l,t} + \beta_2\, Shorter\ Disaster_{l,t} \\ &+ \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}, \end{aligned} \tag{6}$$

$Longer\ Disaster_{l,t}$ is an indicator variable that takes the value of one if county l experienced any CND lasting more than 30 days in year t, and zero otherwise. Similarly, $Shorter\ Disaster_{l,t}$ is an indicator variable that takes the value of one if county l experienced any CND lasting 30 days or less in year t, and zero otherwise.

Panel C of Table OA4 reports the results of estimating equation (2) for public and private firms separately. The results are qualitatively similar to our main specifications, with a few additional insights. For manufacturing firms, longer-duration disasters appear to have a positive association with sales growth, suggesting that the overall negative association between climate disasters and manufacturing firms' operations is driven by short-duration events.

This pattern may reflect two mechanisms. First, longer-lasting disasters tend to cause greater physical damage, which subsequently increases demand for manufactured inputs used in rebuilding and repairs. Because we observe only year-on-year sales changes, our estimates may capture both the initial disruption and the subsequent recovery-driven demand. If rebuilding demand outweighs initial losses over the annual window, longer disasters could show net positive effects. Second, manufacturing firms often serve customers beyond the immediately affected area, allowing them to benefit from post-disaster demand while avoiding prolonged local disruption.

We find a similar pattern for consumer nondurables, where short-term disasters are negatively associated with sales, whereas longer CNDs are positively associated. This is consistent with shorter disasters causing short-run business interruptions. However, longer disasters are more likely to generate increased demand during rebuilding and restocking, and this effect dominates.

Table OA4 (Continued): Impact of CND – Based on CND Characteristics

Panel C: Impact of all CND on Public vs Private firms: Based on Disaster Duration

	Public Firms			Private Firms		
Industry	N (1)	*Longer Disasters* (2)	*Shorter Disasters* (3)	N (4)	*Longer Disasters* (5)	*Shorter Disasters* (6)
All	2,960,229	0.001	−0.000	24,380,197	−0.010***	−0.007***
		(1.17)	(−0.58)		(−20.24)	(−29.97)
Manufacturing	61,190	0.018**	−0.006	549,858	0.045***	−0.025***
		(2.07)	(−1.45)		(17.83)	(−18.56)
Shops	1,526,834	−0.001	−0.000	8,060,130	−0.003***	−0.004***
		(−0.52)	(−0.29)		(−3.67)	(−9.17)
Chemicals	12,231	−0.003	−0.025***	24,299	−0.011	−0.011*
		(−0.22)	(−3.23)		(−0.88)	(−1.79)
Energy	19,715	−0.022	−0.001	58,083	0.039***	0.002
		(−1.51)	(−0.19)		(4.06)	(0.36)
Business Equipment	40,978	0.004	0.012**	253,792	0.026***	0.013***
		(0.52)	(2.41)		(6.70)	(6.30)
Telecom	82,701	0.009	0.001	150,282	0.019***	0.020***
		(1.42)	(0.29)		(3.18)	(6.47)
Utilities	21,375	−0.004	−0.001	58,737	0.015*	0.003
		(−0.21)	(−0.18)		(1.68)	(0.84)
Healthcare	100,485	−0.006	−0.009*	3,625,821	−0.078***	−0.031***
		(−0.93)	(−1.95)		(−76.40)	(−59.82)
Consumer Nondurables	49,583	−0.002	−0.001	862,313	0.045***	−0.003**
		(−0.26)	(−0.18)		(17.34)	(−2.02)
Consumer Durables	13,059	−0.003	−0.001	120,455	0.121***	−0.030***
		(−0.17)	(−0.05)		(20.37)	(−9.33)
Finance	416,766	0.011***	0.003*	2,316,561	−0.003**	0.007***
		(3.69)	(1.72)		(−1.96)	(9.66)
Other	606,275	−0.002	−0.002	7,875,185	−0.001	−0.001**
		(−0.59)	(−1.57)		(−1.33)	(−2.26)
Parent Firm FE, County FE, Year FE	Yes					
Clustering	Parent Firm level					

Panel C presents regression summary statistics from estimating $Change\_Sales_{i,t,l,j} = \alpha + \beta_1\, Longer\ Disaster_{l,t} + \beta_2\, Shorter\ Disaster_{l,t} +$ Parent Firm FE + Year FE + County FE $+ \varepsilon_{i,t}$. *Longer Disaster*$_{l,t}$ is an indicator equal to one if county l experienced any CND lasting more than 30 days in year t, and zero otherwise. *Shorter Disaster*$_{l,t}$ is an indicator equal to one if county l experienced any CND lasting 30 days or less in year t, and zero otherwise. *, **, *** denote significance at the 10%, 5%, 1% levels. T-statistics in parentheses; standard errors clustered at the parent firm level. All variable definitions in Online Appendix OA1.

OA4.3 Disaster Predictability

Lastly, we examine whether the association between sales growth and CND exposure differs based on predictability. Predictable disasters may have smaller impacts because firms can prepare in advance, such as securing inventory, arranging backup suppliers, or taking protective measures. In contrast, unpredictable events may catch firms off guard, leading to larger disruptions. We define predictable CND as events in which the state experienced the same type of CND during the same month in the previous year. We estimate the following equation:

$$\begin{aligned} Change\_Sales_{i,t,l,j} = \alpha + \beta_1\, Predictable\, Disaster_{l,t} + \beta_2\, Unpredictable\, Disaster_{l,t} \\ + \text{Parent Firm FE} + \text{Year FE} + \text{County FE} + \varepsilon_{i,t}. \end{aligned} \tag{7}$$

$Predictable\, Disaster_{l,t}$ ($Unpredictable\, Disaster_{l,t}$) is an indicator variable that takes the value of one if county l experienced any predictable (unpredictable) CND in year t, and zero otherwise. Panel D of Table OA4 presents the results of estimating equation (3). Consistent with prior results, public firms show little sensitivity to predictable or unpredictable disasters, but private firms display clear industry-specific responses. Sectors such as manufacturing, retail, energy services, and healthcare experience notable sales declines, with manufacturing, energy, and consumer durables exhibiting larger declines under predictable disasters and healthcare exhibiting larger declines under unpredictable disasters. The aggregate (All) private-firm response is also slightly larger for unpredictable events. In contrast, industries tied to repair, replacement, or essential consumption such as business equipment, telecom, and consumer nondurables see higher sales following disaster events, with stronger effect for unpredictable disasters. Overall, the results suggest that private firms' sales responses to CNDs are heterogeneous in predictability. Positive demand-driven responses are amplified for unpredictable disasters, while negative supply-side disruptions in capital-intensive sectors can be amplified for predictable disasters as well.

Table OA4 (Continued): Impact of CND – Based on CND Characteristics

Panel D: Impact of all CND on Public vs Private firms: Based on Disaster Predictability

	Public Firms			Private Firms		
Industry	N (1)	*Predictable Disasters* (2)	*Unpredictable Disasters* (3)	N (4)	*Predictable Disasters* (5)	*Unpredictable Disasters* (6)
All	2,960,229	-0.004^{**}	0.001	24,380,197	-0.005^{***}	-0.007^{***}
		(-2.16)	(0.77)		(-5.05)	(-31.78)
Manufacturing	61,190	-0.018	0.001	549,858	-0.034^{***}	-0.010^{***}
		(-1.52)	(0.31)		(-7.02)	(-7.81)
Shops	1,526,834	-0.002	-0.000	8,060,130	-0.006^{***}	-0.004^{***}
		(-0.87)	(-0.28)		(-3.48)	(-9.28)
Chemicals	12,231	-0.075^{***}	-0.015^{**}	24,299	-0.016	-0.010
		(-2.68)	(-2.02)		(-0.64)	(-1.54)
Energy	19,715	0.002	-0.007	58,083	-0.042^{**}	0.007
		(0.08)	(-0.96)		(-2.17)	(1.56)
Business Equipment	40,978	0.025	0.009^{**}	253,792	0.001	0.015^{***}
		(1.26)	(2.03)		(0.13)	(7.33)
Telecom	82,701	0.007	0.001	150,282	0.018	0.018^{***}
		(0.83)	(0.36)		(1.44)	(6.08)
Utilities	21,375	-0.002	0.002	58,737	-0.004	0.002
		(-0.07)	(0.27)		(-0.30)	(0.66)
Healthcare	100,485	-0.021	-0.008^{**}	3,625,821	-0.034^{***}	-0.039^{***}
		(-1.54)	(-2.06)		(-13.41)	(-77.88)
Consumer Nondurables	49,583	-0.018	0.000	862,313	0.011^{**}	0.012^{***}
		(-0.92)	(0.07)		(2.21)	(10.02)
Consumer Durables	13,059	0.034	-0.005	120,455	-0.029^{**}	-0.003
		(1.25)	(-0.29)		(-2.33)	(-0.86)
Finance	416,766	-0.001	0.006^{***}	2,316,561	-0.003	0.006^{***}
		(-0.15)	(3.43)		(-0.97)	(7.36)
Other	606,275	-0.009^{**}	-0.001	7,875,185	0.007^{***}	-0.001^{**}
		(-2.22)	(-0.87)		(4.19)	(-2.05)
Parent Firm FE, County FE, Year FE	Yes					
Clustering	Parent Firm level					

Panel D presents regression summary statistics from estimating $Change\_Sales_{i,t,l,j} = \alpha + \beta_1\, Predictable\, Disaster_{l,t} + \beta_2\, Unpredictable\, Disaster_{l,t} +$ Parent Firm FE + Year FE + County FE + $\varepsilon_{i,t}$. *Predictable Disaster*$_{l,t}$ (*Unpredictable Disaster*$_{l,t}$) is an indicator equal to one if county l experienced any predictable (unpredictable) CND in year t, and zero otherwise. Predictable CND is defined as events in which the state experienced the same type of CND during the same month in the previous year. *, **, *** denote significance at the 10%, 5%, 1% levels. T-statistics in parentheses; standard errors clustered at the parent firm level. All variable definitions in Online Appendix OA1.

OA5. Stock Market Reactions to Climate Disasters

Our primary analyses examine operating performance, which is directly comparable across public and private firms. However, for public firms, we can also examine stock market reactions, which provide insight into how investors perceive climate risk exposure. If investors view climate disasters as materially threatening to public firm value, we would expect significant negative abnormal returns around disaster events. Alternatively, if investors recognize that public firms are sufficiently diversified to absorb localized shocks, stock price reactions may be muted. This analysis complements our operating performance tests and helps assess whether the null operating effects we document are anticipated by capital markets.

To assess investor responses for public firms to these extreme weather events, we examine industry-adjusted abnormal returns around CND. Industry adjusted abnormal returns ($Abnormal\,Return_{i,t}$) represents the daily return for firm i on day t minus the equally weighted return of all the firms in the same Fama-French 12-industry as firm i. Panel A of Table OA5.1 presents descriptive statistics at the firm-date level for the event study analysis sample. Our sample consists of all publicly listed firms with stock return data on CRSP and non-missing data firm-level controls. To limit the influence of extreme observations, we trim all the continuous variables to a 99% level. On average, CND impacts 6% of the firm dates from 1997 to 2022.

We first examine the market reaction to a firm's exposure to CND following Christensen et al. (2020). We use a pooled OLS panel regression that compares daily, firm-level abnormal returns for firms impacted by CND and remaining firms:

$$\begin{aligned} Abnormal\,Return_{i,t} = \alpha + \beta_1\, Event\_pre20_{i,t} + \beta_2\, Event\,Window_{i,t} + \beta_3\, Event\_post20_{i,t} \\ + \theta X_{i,t} + \text{Firm FE} + \text{Date FE} + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

$Abnormal\,Return_{i,t}$ is the daily industry-adjusted abnormal return for firm i on day t. $Event\,Window_{i,t}$, the primary variable of interest, is an indicator equal to one if day t is in the event window and any of the firm's business units are located in the county impacted by CND. We use two event windows: a shorter window of Event$[-1, +1]$ (i.e., the three days from $t-1$ to $t+1$ where t is the first trading date post-CND) and a longer window of Event$[-5, +5]$ (i.e., the eleven days from $t-5$ to $t+5$). $Event\_pre20_{i,t}$ ($Event\_post20_{i,t}$) is an indicator equal to one in the 20 days before (after) the event window for firms whose business units are located in the county impacted by CND and zero otherwise. The extended window helps us to account for any anticipation of the CND and delayed response. The variable $X_{i,t}$ represents a vector of controls including size (natural log of market capitalization as of date t), return on assets (earnings before interest and tax divided by total assets), leverage (total debt divided by total assets), and MB (market-to-book ratio). We include firm and date fixed effects to control for time-invariant firm characteristics and contemporaneous market-wide news and macroeconomic conditions. This specification leverages within-firm variation over time, comparing each firm's abnormal returns during and around the event window to its own non-event days. We cluster standard errors by date and firm.

OA5.1 Average Results

Panel B of Table OA5.1 reports the results of estimating Equation (8) for stock market reactions to climate disasters. Columns (1) and (2) present results for the three-day event window. The coefficient on Event$[-1,+1]$ is negative and statistically significant at the 1% level, indicating that a severe weather event reduces an affected firm's market capitalization by approximately 1.3%. While statistically significant, this magnitude is economically modest, a 1.3% decline is well within the range of normal daily volatility for most stocks and represents a small fraction of firm value.

To assess whether markets overreact to disaster news and subsequently correct (Huynh and Xia, 2021), we also examine a longer event window spanning five days before and after the event date. The coefficient on Event$[-5,+5]$ remains negative and statistically significant, with magnitudes ranging from -1.2% to -1.3%. The similarity between short and long windows suggests limited reversal, but the persistently modest magnitude reinforces that climate disasters do not cause substantial value destruction for the average public firm.

OA5.2 Industry based variation

The modest average effect may mask heterogeneity across industries. We next then examine whether the association between abnormal return over a one-day event window and CND exposure differs at the industry level. Addoum et al. (2023) argue that CND can affect firms differently based on their industry membership. We use the Fama-French 12 industry classifications to construct subsamples at the firm-county-industry level.

Panel A of Table OA5.2 indicates that the worst hit sector is other categories (−3.2%), followed by consumer durables (−3%), business equipment (−2.3%), manufacturing (−1.6%), and shops (−1.5%).[19] In Panel B of Table OA5.2, we consider longer five-day event windows. The results are similar and are driven by firms in consumer durables, manufacturing, business equipment, and other categories. One potential reason could be that the goods or services (such as automobiles, machinery, furniture, and hotels) provided by these sectors are discretionary, in that demand elasticity for products of such industries is high. When consumers experience a negative event, such as a CND, they may postpone the purchase of these goods or services either due to a loss in wealth or increased precautionary savings resulting from a change in risk perception (Liu and Strahilevitz, 2025). This, in turn, could lead to a decline in revenue for businesses operating within these sectors. Overall, the negative stock market reactions appear to be driven by certain industries, such as consumer durables, manufacturing, and business equipment.

OA5.3 Variation Based on Type of CND

We examine whether the association between abnormal returns and CND exposure differs based on CND characteristics. First, we look at the type of CND by segregating CND into five categories: named disasters, coastal storms, fires, other storms, and floods.[20] Table OA5.3 reports the results of estimating Equation (8) for each of the five CNDs separately. The results indicate that named disasters (−2.8%) and floods (−2.3%) drive the negative association between the 11-day abnormal return and the CND. The evidence suggests that only a subset of disaster types meaningfully affects firm returns.

OA5.4 Variation Based on CND Duration

Next, we examine whether longer or shorter duration CND has a differential impact on the market's reaction. We divide the CND sample into two categories: CND lasting more than 30 days (longer CND) and CND lasting 30 days or less (shorter CND). Table OA5.4 reports the results of estimating Equation (8) for these two categories separately. The results indicate that a shorter

[19]Other categories include firms that do not fall under any of the remaining 11 categories, including firms operating in sectors such as mining, construction, building materials, transportation, hotels, business services, and entertainment.

[20]These are tropical storms which are given unique names by FEMA, such as Hurricane Katrina, Ian, and others.

CND drives the negative association between the 11-day abnormal return and the CND. In the case of a more prolonged CND, we find negative and statistically significant associations only in the post-event period but not during the event window. This finding could indicate that the market reacts promptly to a shorter CND but takes time to ascertain the impact of a more prolonged CND on a firm's performance.

OA5.5 Variation Based on CND Predictability

Next, we examine whether the association between abnormal returns and CND exposure differs based on predictability. Predictable disasters may elicit smaller market reactions for two reasons. First, firms with predictable CND exposure are better equipped to hedge or mitigate risks, reducing actual damage. Second, investors may already impound predictable climate risks into prices, limiting the information content of disaster announcements. In contrast, unpredictable CND events may catch both firms and investors off guard, leading to larger price reactions. We define predictable CND as events in which the state experienced the same type of CND during the same month in the previous year.[21]

Table OA5.5 presents the results of estimating Equation (8) for predictable and unpredictable CNDs separately. The findings show that firms exposed to predictable CNDs experience a significant 2.2% decline in market value during the $[-5, +5]$ event window, as indicated in Column (2), although the effect diminishes afterward. In Column (1), there is no significant market reaction during the $[-1, +1]$ event window, but there is a negative market reaction afterward, which, when combined with the result in Column (2), suggests that the market reaction is primarily concentrated in the $[-5, +5]$ window. In contrast, unpredictable CNDs are associated with a smaller 1.3% decline in the event window, followed by an additional 0.7% drop over the subsequent 20 days. The results show a pronounced negative effect both during and after the event, with strong statistical significance in both the immediate and extended windows. This persistent adverse reaction indicates the challenges of market adaptation to unforeseen events, where uncertainty leads to prolonged adjustment periods. The results suggest that, while predictable disasters allow for preemptive

[21] Additionally, to assess the degree to which our results are driven by the predictability of hurricanes in Florida, in an untabulated test, we re-estimate the results from Table OA5.1 after excluding events related to Florida hurricanes. The results remain robust and consistent after excluding these events.

market reactions, unpredictable events introduce uncertainty, resulting in longer lasting economic impact, as measured by stock returns of the affected firms.

OA5.6 Summary of Stock Market Findings

Taken together, our stock market analyses reveal that climate disasters have modest and concentrated effects on public firm valuations. The average market reaction of 1.3% is economically small and driven by specific industries (consumer durables, manufacturing, business equipment) and disaster types (named storms, floods). Most industry and disaster type combinations show no significant stock price response. Longer duration disasters show delayed rather than immediate reactions, and predictable disasters elicit responses concentrated in the event window while unpredictable disasters generate more persistent effects. Overall, these findings are consistent with our operating performance results: public firms appear resilient to climate disasters, with effects that are modest in magnitude and heterogeneous across contexts. This resilience stands in stark contrast to private firm vulnerability documented in our sales growth analyses, reinforcing that organizational form and firm size critically determine climate risk exposure.

Table OA5.1: Investor reaction to CND

Panel A: Descriptive Statistics for the Event Study Sample

	N.	Mean	Median	Std. Dev.	P25	P75
Abnormal Return	26,981,202	−0.052	−0.091	2.940	−1.462	1.267
Event Window [−1, +1]	26,981,202	0.019	0	0.135	0	0
Event Window [−5, +5]	26,981,202	0.057	0	0.231	0	0
Ln(ME)	26,981,202	5.973	5.918	1.999	4.481	7.394
Market cap (in $ Mn)	26,981,202	2,402.62	371.74	6,156.35	88.31	1,626.56
Lev	26,981,202	0.211	0.166	0.202	0.028	0.339
ROA	26,981,202	0.009	0.019	0.056	0.004	0.037
MB	26,981,202	2.814	1.815	3.583	1.107	3.249
Disclosure_d	6,339,924	0.509	1	0.500	0	1
CCExposure	13,905,839	0.086	0.030	0.169	0.011	0.076

Table OA5.1 (Continued): Investor reaction to CND

Panel B: Impact of CND on Abnormal Returns

Event Window	Event$[-1,+1]$		Event$[-5,+5]$	
Dependent Variable	*Abnormal Return* (1)	*Abnormal Return* (2)	*Abnormal Return* (3)	*Abnormal Return* (4)
Event_pre20	0.000	0.000	0.002	0.002
	(0.12)	(0.14)	(0.68)	(0.69)
Event Window	-0.013^{***}	-0.013^{***}	-0.013^{***}	-0.012^{***}
	(-3.28)	(-3.19)	(-3.13)	(-3.03)
Event_post20	-0.007^{**}	-0.006^{*}	-0.005	-0.004
	(-2.06)	(-1.94)	(-1.57)	(-1.44)
Ln(ME)		0.135^{***}		0.135^{***}
		(41.72)		(41.72)
Lev		0.051^{***}		0.051^{***}
		(4.70)		(4.70)
ROA		-0.077^{**}		-0.077^{**}
		(-2.06)		(-2.06)
MB		-0.013^{***}		-0.013^{***}
		(-22.60)		(-22.60)
Constant		-0.833^{***}		-0.833^{***}
		(-42.86)		(-42.88)
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of Obs	26,981,202	26,981,202	26,981,202	26,981,202
Adj. R^2	0.004	0.004	0.004	0.004
Clustering	Date and firm level			

The table presents regression summary statistics from estimating the following equation:

$$Abnormal\ Return_{i,t} = \alpha + \beta_1\ Event\_pre20_{i,t} + \beta_2\ Event\,Window_{i,t} + \beta_3\ Event\_post20_{i,t} + \theta X_{i,t} + \text{Firm FE} + \text{Date FE} + \varepsilon_{i,t}.$$

Event Window is *Event*$[-1,+1]$ (i.e., the three-day period from $t-1$ to $t+1$ where t is the first trading date post CND) in column (1)–(2) and *Event*$[-5,+5]$ (i.e., the eleven-day period from $t-5$ to $t+5$ where t is the first trading date post weather event) in column (3)–(4). *Abnormal Return*$_{i,t}$ is the daily industry-adjusted abnormal return for firm i on day t. *Event_pre20*$_{i,t}$ (*Event_post20*$_{i,t}$) is an indicator equal to one for treatment firms in the 20 days before (after) the event window and zero otherwise, and is included to indicate the sharpness of the treatment effect. Panel A presents the distributional statistics for the event study analysis. Panel B presents the results from the regression. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at firm and date level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

Table OA5.2: Investor reaction to CND – Industry Cross-Sectional Analysis

Panel A: 3-day Market Reaction of CND based on Industry

Dependent Variable	*Abnormal Return*											
	CNDu (1)	CDu (2)	Manf (3)	Energy (4)	Chem (5)	Buss Equ (6)	Tele (7)	Utilities (8)	Shops (9)	HC (10)	Finance (11)	Others (12)
Event_pre20	0.003	0.007	0.005	−0.014	−0.013	−0.002	−0.002	0.009	−0.004	0.002	−0.003	0.008
	(0.42)	(0.51)	(0.71)	(−1.14)	(−1.09)	(−0.21)	(−0.14)	(1.12)	(−0.52)	(0.25)	(−0.51)	(1.06)
Event[−1, +1]	−0.008	−0.030*	−0.016**	0.004	−0.012	−0.023**	−0.010	0.004	−0.015**	0.000	0.001	−0.032***
	(−0.80)	(−1.93)	(−1.98)	(0.32)	(−0.89)	(−2.49)	(−0.61)	(0.50)	(−2.04)	(0.02)	(0.19)	(−3.62)
Event_post20	−0.006	−0.023*	−0.012*	−0.014	0.017	0.002	−0.021	0.005	0.001	−0.011	−0.012**	−0.011
	(−0.65)	(−1.73)	(−1.73)	(−1.09)	(1.22)	(0.27)	(−1.30)	(0.57)	(0.20)	(−1.11)	(−1.96)	(−1.42)
Ln(ME)	0.131***	0.156***	0.147***	0.146***	0.157***	0.144***	0.134***	0.078***	0.159***	0.184***	0.139***	0.161***
	(12.10)	(11.57)	(19.24)	(15.58)	(9.67)	(21.98)	(13.82)	(7.09)	(21.38)	(31.18)	(21.88)	(23.38)
Lev	0.175***	0.173***	0.130***	−0.016	0.158***	0.067***	0.055	0.046	0.067**	0.045*	−0.025	0.072***
	(4.42)	(3.14)	(4.57)	(−0.36)	(3.12)	(2.76)	(1.17)	(0.78)	(2.09)	(1.93)	(−0.93)	(2.72)
ROA	−0.225	−0.169	−0.511***	0.014	−0.307	0.065	0.629**	−0.203	−0.351***	−0.414***	−0.127	−0.161
	(−1.42)	(−0.79)	(−3.91)	(0.10)	(−1.29)	(0.79)	(2.42)	(−0.76)	(−2.70)	(−7.25)	(−0.72)	(−1.61)
MB	−0.014***	−0.012***	−0.014***	−0.011***	−0.013***	−0.012***	−0.008***	−0.009**	−0.014***	−0.013***	−0.021***	−0.014***
	(−8.42)	(−4.60)	(−8.24)	(−5.68)	(−5.86)	(−10.66)	(−4.96)	(−2.39)	(−8.91)	(−16.35)	(−8.64)	(−11.83)
Constant	−0.832***	−0.977***	−0.914***	−0.985***	−1.091***	−0.893***	−0.948***	−0.588***	−0.965***	−1.095***	−0.750***	−0.998***
	(−12.59)	(−12.53)	(−19.80)	(−15.05)	(−10.10)	(−23.13)	(−14.85)	(−6.53)	(−21.57)	(−32.96)	(−21.63)	(−23.68)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	1,203,604	614,968	2,491,203	1,201,544	581,661	4,808,764	764,821	815,114	2,362,137	3,271,997	4,889,817	3,975,563
Adj. R^2	0.003	0.006	0.004	0.008	0.007	0.006	0.007	−0.000	0.004	0.006	0.013	0.006
Clustering	Date and firm level											

Table OA5.2 (Continued): Investor reaction to CND – Industry Cross-Sectional Analysis

Panel B: 11-day Market Reaction of CND based on Industry

Dependent Variable	*Abnormal Return*											
	CNDu (1)	CDu (2)	Manf (3)	Energy (4)	Chem (5)	Buss Equ (6)	Tele (7)	Utilities (8)	Shops (9)	HC (10)	Finance (11)	Others (12)
Event_pre20	−0.001	0.004	0.004	−0.020*	−0.008	0.000	0.002	0.004	0.000	0.007	0.002	0.011
	(−0.18)	(0.30)	(0.63)	(−1.70)	(−0.72)	(0.06)	(0.12)	(0.52)	(0.03)	(0.76)	(0.39)	(1.51)
Event[−5, +5]	−0.009	−0.033**	−0.016**	0.003	−0.013	−0.022**	−0.010	0.003	−0.013	0.001	0.003	−0.030***
	(−0.85)	(−2.06)	(−1.97)	(0.22)	(−0.91)	(−2.35)	(−0.59)	(0.36)	(−1.63)	(0.07)	(0.39)	(−3.46)
Event_post20	−0.003	−0.028**	−0.010	−0.011	0.010	0.009	−0.020	−0.000	0.006	−0.011	−0.008	−0.008
	(−0.30)	(−2.27)	(−1.55)	(−0.89)	(0.79)	(1.19)	(−1.39)	(−0.01)	(0.91)	(−1.23)	(−1.39)	(−1.17)
Ln(ME)	0.131***	0.156***	0.147***	0.146***	0.157***	0.145***	0.134***	0.078***	0.159***	0.184***	0.139***	0.161***
	(12.10)	(11.57)	(19.24)	(15.58)	(9.67)	(21.98)	(13.82)	(7.09)	(21.37)	(31.18)	(21.88)	(23.38)
Lev	0.175***	0.172***	0.130***	−0.016	0.158***	0.067***	0.055	0.046	0.067**	0.045*	−0.026	0.072***
	(4.42)	(3.14)	(4.57)	(−0.36)	(3.12)	(2.76)	(1.17)	(0.79)	(2.08)	(1.93)	(−0.93)	(2.71)
ROA	−0.225	−0.169	−0.511***	0.014	−0.307	0.065	0.628**	−0.203	−0.350***	−0.414***	−0.127	−0.161
	(−1.42)	(−0.79)	(−3.91)	(0.10)	(−1.29)	(0.79)	(2.42)	(−0.76)	(−2.70)	(−7.25)	(−0.72)	(−1.61)
MB	−0.014***	−0.012***	−0.014***	−0.011***	−0.013***	−0.012***	−0.008***	−0.009**	−0.014***	−0.013***	−0.021***	−0.014***
	(−8.42)	(−4.60)	(−8.24)	(−5.69)	(−5.86)	(−10.66)	(−4.96)	(−2.40)	(−8.91)	(−16.35)	(−8.64)	(−11.83)
Constant	−0.831***	−0.976***	−0.914***	−0.984***	−1.091***	−0.894***	−0.948***	−0.587***	−0.966***	−1.095***	−0.750***	−0.999***
	(−12.58)	(−12.52)	(−19.80)	(−15.05)	(−10.10)	(−23.14)	(−14.85)	(−6.53)	(−21.59)	(−32.96)	(−21.65)	(−23.69)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	1,203,604	614,968	2,491,203	1,201,544	581,661	4,808,764	764,821	815,114	2,362,137	3,271,997	4,889,817	3,975,563
Adj. R^2	0.003	0.006	0.004	0.008	0.007	0.006	0.007	−0.000	0.004	0.006	0.013	0.006
Clustering	Date and firm level											

All panels present regression summary statistics from estimating the following equation:

$$Abnormal\ Return_{i,t} = \alpha + \beta_1\, Event\_pre20_{i,t} + \beta_2\, Event\,Window_{i,t} + \beta_3\, Event\_post20_{i,t} + \theta X_{i,t} + \text{Firm FE} + \text{Date FE} + \varepsilon_{i,t}.$$

Event Window is *Event*[−1, +1] (i.e., the three-day period from $t-1$ to $t+1$, where t is the first trading date post-CND) in Panel A and *Event*[−5, +5] (i.e., the eleven-day period from $t-5$ to $t+5$) in Panel B. Within each panel, results are presented separately for each of the Fama-French 12-industry classifications (in the order of the presentation): Consumer Nondurables (CNDu), Consumer Durables (CDu), Manufacturing (Manf), Energy, Chemicals (Chem), Business equipment (Buss Equ), Telecom (Tele), Utilities, Shops, Healthcare (HC), Finance and Others. $Abnormal\ Return_{i,t}$ is the daily industry-adjusted abnormal return for firm i on day t. $Event\_pre20_{i,t}$ ($Event\_post20_{i,t}$) is an indicator equal to one for treatment firms in the 20 days before (after) the event window and zero otherwise, and is included to indicate the sharpness of the treatment effect. The controls include size (natural log of market capitalization as on date t), Return on Assets (earnings before interest and tax divided by total assets), leverage (total debt divided by total assets), and market-to-book ratio (MB). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at firm and date level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

Table OA5.3: Investor reaction to CND based on CND Type

Dependent Variable	*Abnormal Return*									
Disaster Type	Named Disasters		Coastal Storms		Fires		Other Storms		Floods	
Event Window	E[−1, +1] (1)	E[−5, +5] (2)	E[−1, +1] (3)	E[−5, +5] (4)	E[−1, +1] (5)	E[−5, +5] (6)	E[−1, +1] (7)	E[−5, +5] (8)	E[−1, +1] (9)	E[−5, +5] (10)
Event_pre20	−0.010	−0.009	0.036	0.000	0.009	0.001	0.004	0.007*	−0.005	0.001
	(−1.22)	(−1.16)	(0.75)	(0.01)	(0.75)	(0.05)	(1.05)	(1.89)	(−0.73)	(0.16)
Event Window	−0.023	−0.028***	0.044	0.006	0.010	0.017	0.000	−0.007	−0.015	−0.023***
	(−1.33)	(−2.64)	(0.52)	(0.12)	(0.31)	(0.97)	(0.05)	(−1.44)	(−1.07)	(−2.68)
Event_post20	−0.005	0.007	0.013	0.024	0.006	0.003	−0.010***	−0.010**	−0.019**	−0.011
	(−0.66)	(0.85)	(0.34)	(0.71)	(0.50)	(0.23)	(−2.62)	(−2.49)	(−2.43)	(−1.31)
Ln(ME)	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***	0.135***
	(41.73)	(41.73)	(41.75)	(41.75)	(41.74)	(41.74)	(41.75)	(41.75)	(41.74)	(41.74)
Lev	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***	0.051***
	(4.68)	(4.68)	(4.68)	(4.68)	(4.68)	(4.68)	(4.69)	(4.69)	(4.70)	(4.70)
ROA	−0.080**	−0.080**	−0.080**	−0.080**	−0.079**	−0.079**	−0.078**	−0.078**	−0.079**	−0.079**
	(−2.11)	(−2.11)	(−2.12)	(−2.12)	(−2.10)	(−2.10)	(−2.07)	(−2.07)	(−2.10)	(−2.10)
MB	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***	−0.013***
	(−22.64)	(−22.64)	(−22.64)	(−22.64)	(−22.64)	(−22.64)	(−22.63)	(−22.64)	(−22.63)	(−22.63)
Constant	−0.834***	−0.834***	−0.835***	−0.835***	−0.835***	−0.835***	−0.834***	−0.834***	−0.835***	−0.835***
	(−42.93)	(−42.93)	(−42.98)	(−42.98)	(−42.98)	(−42.98)	(−42.99)	(−42.98)	(−42.97)	(−42.98)
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs	26,799,975	26,799,975	26,764,328	26,764,328	26,772,273	26,772,273	26,869,995	26,869,995	26,785,258	26,785,258
Adj. R^2	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
Clustering	Date and firm level									

The table presents regression summary statistics from estimating the following equation separately for five types of CND: Named Disasters, Coastal Storms, Fires, Other Storms, and Floods:

$$Abnormal\ Return_{i,t} = \alpha + \beta_1\, Event\_pre20_{i,t} + \beta_2\, Event\,Window_{i,t} + \beta_3\, Event\_post20_{i,t}$$
$$+\, \theta X_{i,t} + \text{Firm FE} + \text{Date FE} + \varepsilon_{i,t}.$$

Within each subsample, results are presented for both *Event*$[-1,+1]$ (i.e., the three-day period from $t-1$ to $t+1$ where t is the first trading date post CND) and *Event*$[-5,+5]$ (i.e., the eleven-day period from $t-5$ to $t+5$ where t is the first trading date post CND). *Abnormal Return*$_{i,t}$ is the daily industry-adjusted abnormal return for firm i on day t. *Event_pre20*$_{i,t}$ (*Event_post20*$_{i,t}$) is an indicator equal to one for treatment firms in the 20 days before (after) the event window and zero otherwise, and is included to indicate the sharpness of the treatment effect. The controls include size (natural log of market capitalization as on date t), Return on Assets (earnings before interest and tax divided by total assets), leverage (total debt divided by total assets), and market-to-book ratio (MB). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at firm and date level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

Table OA5.4: Investor reaction to CND based on CND Duration

Dependent Variable	*Abnormal Return*			
Disaster Duration	Longer Disasters		Shorter Disasters	
	Event[−1, +1] (1)	Event[−5, +5] (2)	Event[−1, +1] (3)	Event[−5, +5] (4)
Event_pre20	0.009	0.005	0.000	0.003
	(1.46)	(0.89)	(0.03)	(0.74)
Event Window	0.002	−0.003	−0.009	−0.014***
	(0.18)	(−0.33)	(−1.27)	(−2.99)
Event_post20	−0.018***	−0.016***	−0.009**	−0.004
	(−3.21)	(−2.78)	(−2.44)	(−1.19)
Ln(ME)	0.135***	0.135***	0.135***	0.135***
	(41.74)	(41.74)	(41.73)	(41.73)
Lev	0.051***	0.051***	0.051***	0.051***
	(4.68)	(4.68)	(4.71)	(4.71)
ROA	−0.079**	−0.079**	−0.077**	−0.078**
	(−2.10)	(−2.10)	(−2.06)	(−2.06)
MB	−0.013***	−0.013***	−0.013***	−0.013***
	(−22.63)	(−22.63)	(−22.64)	(−22.64)
Constant	−0.834***	−0.834***	−0.833***	−0.833***
	(−42.97)	(−42.97)	(−42.93)	(−42.93)
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of Obs	26,805,935	26,805,935	26,896,136	26,896,136
Adj. R^2	0.004	0.004	0.004	0.004
Clustering	Date and firm level			

The table presents regression summary statistics from estimating the following equation separately for Longer Disasters (Disaster Duration > 30 days) and Shorter Disasters (Disaster Duration ≤ 30 days):

$$Abnormal\,Return_{i,t} = \alpha + \beta_1\, Event\_pre20_{i,t} + \beta_2\, Event\,Window_{i,t} + \beta_3\, Event\_post20_{i,t} + \theta X_{i,t} + \text{Firm FE} + \text{Date FE} + \varepsilon_{i,t}.$$

Within each subsample, results are presented for both *Event*[−1, +1] (i.e., the three-day period from $t-1$ to $t+1$ where t is the first trading date post CND) and *Event*[−5, +5] (i.e., the eleven-day period from $t-5$ to $t+5$ where t is the first trading date post CND). *Abnormal Return*$_{i,t}$ is the daily industry-adjusted abnormal return for firm i on day t. *Event_pre20*$_{i,t}$ (*Event_post20*$_{i,t}$) is an indicator equal to one for treatment firms in the 20 days before (after) the event window and zero otherwise, and is included to indicate the sharpness of the treatment effect. The controls include size (natural log of market capitalization as on date t), Return on Assets (earnings before interest and tax divided by total assets), leverage (total debt divided by total assets), and market-to-book ratio (MB). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at firm and date level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

Table OA5.5: Investor reaction to CND based on CND Predictability

Dependent Variable	*Abnormal Return*			
Disaster Predictability	Predictable Disasters		Unpredictable Disasters	
	Event$[-1,+1]$ (1)	Event$[-5,+5]$ (2)	Event$[-1,+1]$ (3)	Event$[-5,+5]$ (4)
Event_pre20	0.001	0.004	0.000	0.002
	(0.10)	(0.51)	(0.05)	(0.48)
Event Window	-0.019	-0.022^{**}	-0.003	-0.013^{***}
	(-1.09)	(-2.21)	(-0.48)	(-2.95)
Event_post20	-0.015^{*}	-0.000	-0.010^{***}	-0.007^{**}
	(-1.90)	(-0.00)	(-3.09)	(-2.09)
Ln(ME)	0.135^{***}	0.135^{***}	0.135^{***}	0.135^{***}
	(41.74)	(41.74)	(41.74)	(41.74)
Lev	0.051^{***}	0.051^{***}	0.051^{***}	0.051^{***}
	(4.67)	(4.67)	(4.72)	(4.72)
ROA	-0.079^{**}	-0.079^{**}	-0.077^{**}	-0.077^{**}
	(-2.11)	(-2.11)	(-2.05)	(-2.05)
MB	-0.013^{***}	-0.013^{***}	-0.013^{***}	-0.013^{***}
	(-22.64)	(-22.64)	(-22.63)	(-22.64)
Constant	-0.834^{***}	-0.834^{***}	-0.833^{***}	-0.833^{***}
	(-42.97)	(-42.97)	(-42.93)	(-42.93)
Date FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
No. of Obs	26,781,265	26,781,265	26,915,110	26,915,110
Adj. R^2	0.004	0.004	0.004	0.004
Clustering	Date and firm level			

All panels present regression summary statistics from estimating the following equation separately for predictable CND (events in which the state experienced the same type of CND during the same month in the previous year) and unpredictable CND:

$$\begin{aligned} Abnormal\,Return_{i,t} &= \alpha + \beta_1\,Event\_pre20_{i,t} + \beta_2\,Event\,Window_{i,t} + \beta_3\,Event\_post20_{i,t} \\ &+ \theta X_{i,t} + \text{Firm FE} + \text{Date FE} + \varepsilon_{i,t}. \end{aligned}$$

Within each subsample, results are presented for both *Event*$[-1,+1]$ (i.e., the three-day period from $t-1$ to $t+1$ where t is the first trading date post CND) and *Event*$[-5,+5]$ (i.e., the eleven-day period from $t-5$ to $t+5$ where t is the first trading date post CND). *Abnormal* $Return_{i,t}$ is the daily industry-adjusted abnormal return for firm i on day t. $Event\_pre20_{i,t}$ ($Event\_post20_{i,t}$) is an indicator equal to one for treatment firms in the 20 days before (after) the event window and zero otherwise, and is included to indicate the sharpness of the treatment effect. The controls include size (natural log of market capitalization as on date t), Return on Assets (earnings before interest and tax divided by total assets), leverage (total debt divided by total assets), and market-to-book ratio (MB). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at firm and date level. T-statistics are reported in parentheses. All variable definitions appear in Online Appendix OA1.

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